DELFT UNIVERSITY OF TECHNOLOGY

MASTER IN CIVIL ENGINEERING, TRACK: TRANSPORT & PLANNING

MSC THESIS

Traffic safety through Cooperative Automated Vehicle 'herd immunity'

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Preface

This master's thesis 'Traffic Safety Through Cooperative Automated Vehicle 'Herd Immunity" is a proof of concept for herd immunity in car traffic. The idea that the concept of herd immunity could function for car traffic immediately grabbed my attention as I was looking for possible topics to graduate in. Combining a number of topics that interest me I was enthralled by how this concept would function realistically. This thesis is written for my master's graduation in Transport & Planning at the faculty of Civil Engineering and Geosciences at the Delft University of Technology. This thesis was executed from April 2021 till January 2022. Throughout this process a number of people have been absolutely incredible in helping me cross the finish line.

I am profoundly grateful to Simeon Calvert, my daily supervisor, who managed to give me focus when there was otherwise none to be found. Our meetings always left me thinking critically of my work and raised the academic level. Through thick and thin, regardless of COVID-19, he was able to motivate me and provide critical feedback. Next I would like to thank Eleonora Papadimitriou, my external supervisor, for going above and beyond for what an external supervisor should take on her plate. She helped me immensely with the set up of my report and keeping the big picture in mind. Although she might not always agree with simulation for safety purposes, she kept bias aside and was an incredible help. Lastly I would like to thank my chair, Bart van Arem, for providing critical discussion points during presentations and meetings. With his tremendous experience I was pointed towards the right direction and I was able to scope my project appropriately.

Due to COVID-19 it has not been the smoothest process graduating at the Delft University of Technology, but a number of people helped keep my sanity at a healthy level. Brian and Eline provided the much needed coffee breaks and Olympics streams. Daphne, you were there when I needed someone to rant at and with. Igor, we talked about everything and nothing, and that's often exactly what I needed. Another thanks goes out to Ivo, who helped me keep a healthy perspective and played more than enough chess with me. Finally, a special thanks goes out to my mom, who helped me pick the topic, as well as providing brilliantly fancy lunches even if it was never the most convenient for her.

This topic has helped broaden my knowledge on traffic safety and cooperative automated vehicles. I'm very curious to see this work be continued by others and to see what conclusions it brings them.

SUMMARY

The research of connected automated vehicles (CAVs) is an emerging topic within the field of transport & planning. It is not a question of whether the vehicles will be available for commercial use, but rather a question of when they will arrive. The safety of these vehicles is a necessary and ongoing discussion. In current research, a consensus is reached that crashes occur mainly due to human error. This human error is either due to negligence of the driving activity, like drunk driving or texting while driving, or due to incorrect decision making at critical moments. This study focuses on the topic of traffic safety with the principle of herd immunity in mind. It is theorised that crash risk can behave similarly to how a virus behaves (where crash risk is the chance that a crash occurs at a certain point in time). It spreads and infects vulnerable members of the population. The aim of this study is to determine whether the principle of herd immunity can be applied to car traffic, and if so, to what extent they can be compared through an impact assessment. The research question attached to this is: "How is traffic safety influenced by connected (automated) vehicles considering the concept of herd immunity?"

To discover the theorised safety impacts of CAVs, an extensive literature review was performed. Another purpose of the literature review was to determine the effects that separate models could have on a simulation model, and which of these models would be most appropriate for simulating CAVs and human drivers in the same model. The first part of the literature review concerns the principle of herd immunity. Here it is defined as the resistance to infection that a population has due to a proportion of the population having immunity to said virus. The goal of this part of the literature review was to define the mechanisms that make up viral spread and herd immunity. Gaining a better understanding of this topic made it possible to translate it to herd immunity for car traffic. Many of the variables of either principle could translate quite directly, for example; frequency of contact, crash risk/viral load, and traffic volume/agent volume. This could then be connected to traffic safety. Traffic safety as part of the literature review had two functions, one considering which safety metric to use to measure safety in the simulation model, and another to see the general effects of CAVs on traffic safety. The results of this research indicated that CAVs could only provide benefits as most crashes occur due to human inputs or interference. The chosen safety metric for vehicle simulation was safety fields. This safety metric is an underutilised safety metric that has received little attention in previous research because it is a fairly new development in traffic safety, and it is a bit more elaborate to apply than other safety metrics. This safety metric provides much more than a standard safety metric as it incorporates more than just the vehicles on the road, it includes a behavioural field as well as a static field of influence. The behavioural field is especially useful as it helps distinguish between the behaviours of a CAV and a human driver.

The literature review was continued by the research into the different driving behaviours that distinguish a CAV from a human driver. This section of the literature review was especially targeted to the driving behaviour that could be simulated. For that purpose, this part of the literature review was done in tandem with the selection of an appropriate car-following model. These car-following models make use of different parameters to determine their specific driving behaviours. The intelligent driver model+ (IDM+) was chosen as the car-following model because it is a transparent, straightforward model with sufficient distinguishing factors for driving behaviour. Headways and speeds were the main methods in calculating the acceleration and deceleration of the following vehicle. Several other car-following models were considered but IDM+ was considered the most appropriate for the purposes of the research. The driving behaviour of CAVs and human drivers were distinguished by there headways, reaction times, and driving risk. Human drivers were considered to have a driving risk parameter value of 0.4 which is used when calculating the strength of the behavioural field for safety fields, whereas CAVs have a driving risk of 0 because they are assumed to exhibit perfect driving. Reaction times were also set to 0 for CAVs because they can instantly react to the actions of vehicles around them, whereas human drivers have a 1 second reaction time (which is still considered an optimal reaction time). The headways depended on the vehicle order, CAVs following other CAVs have a headway of 0.9 seconds, humans following either type of vehicle had a headway of 1 second, and CAVs following human drivers used a desired headway of 1.5 seconds.

Lane-change models were researched to determine the effects that CAVs could have on the safety when considering lane-changes. Many lane-change models were considered in the literature review and it was agreed that CAVs would provide benefits for lane changing because they do not desire risky manoeuvres. Vehicle crashes occur frequently due to lane-changes and CAVs could lessen that because they are able to take in all surroundings at all times, whereas human attention can only be focused in one direction at a time. The positive effects that CAVs could have on lane-changes is apparent, but for the purpose of this research, they would not be used in the simulation model.

The simulation methodology is based on the decisions made in the literature review. After having chosen the appropriate safety metric, car-following model, and driving behaviours, the simulation model could be created. The methodology describes the design steps of the simulation model. The purpose of the simulation model is to act as an impact assessment for the introduction of CAVs. To do this, all of the decisions made previously had to be incorporated into the model. Depending on the type of vehicle as well as what vehicle they are following, their simulation parameters are different. Attaining statistical significance was also included in this methodology. This was reached by having a specific number of simulation runs which would vary the order at which the vehicles would enter the road. This method of varying the runs was created so that situations with different following situations would arise. Calibration was also included in the methodology to ensure that the simulation inputs would create the most realistic situations. Here several input variables were tested to determine their effects on total simulation time as well as reducing the potential for outliers. Two separate simulation scenarios were designed. One was the baseline scenario which did not include any disturbance, and the second was a single lane scenario with a disturbance being added at a specific location for a certain amount of time. The data analysis was done for the second scenario. Safety fields do not have a unit of measurement which is why it is only possible to compare it with other safety fields values. First, the kinetic safety field strength is shown by Equation 1. The kinetic safety field strength is what is used to find the behavioural field strength, and these two combined create the total safety field strength. The magnitude of the kinetic safety field strength is mainly influenced by the proximity of the leading vehicle as well as the speed of the leading vehicle. These factors along with the virtual mass of the following vehicle make up the safety field strength.

$$\boldsymbol{E}_V = \frac{G \cdot R_c \cdot M_c}{|\boldsymbol{r}_{cj}|^{k_1}} \cdot \frac{\boldsymbol{r}_{cj}}{|\boldsymbol{r}_{cj}|} \cdot e^{(k_3 v_c \cos\theta_c)} \tag{1}$$

Where:

- G: Gravitational constant
- R_c: Road condition influencing factor.
- M_c: Virtual mass of vehicle c.
- r_{cj}: Distance between vehicles.
- k_1 & k_3: undetermined constant greater than zero (Wang *et al.* [1], 2015).
- v_c: Velocity of vehicle c.
- θ_c: Angle between velocity of the leading vehicle and following vehicle.

Equation 2 shows the potential field equation necessary for calculating the total safety field strength. This equation is not used in the simulated scenarios because there are no static objects in the simulations, which foregoes the need for this part of the safety field strength.

$$\boldsymbol{E}_R = \frac{G \cdot R_c \cdot M_c}{\left|\boldsymbol{r}_{cj}\right|^{k_1}} \cdot \frac{\boldsymbol{r}_{cj}}{\left|\boldsymbol{r}_{cj}\right|} \tag{2}$$

Where:

- G: Gravitational constant
- R_c: Road condition influencing factor.
- M_c: Virtual mass of vehicle c.
- r_{cj}: Distance between vehicles.
- k_1 : Undetermined constant greater than zero (Wang *et al.* [1], 2015).

The behaviour field depicted by Equation 3 is what determines the safety field strength due to the behavioural impact. This is done by using the kinetic field strength in combination with a variable called "driving risk". Each driver has a certain value of "driving risk" where the higher the number, the larger negative impact it has on the level of safety.

$$\boldsymbol{E}_D = \boldsymbol{E}_V \cdot DR_c \tag{3}$$

Where:

- $\boldsymbol{E}_{D\_cj}$: Behaviour safety field strength.
- $\boldsymbol{E}_{V\_cj}$: Kinetic safety field strength.
- DR_c: Driver risk (dimensionless value between 0 and 1).

$$\boldsymbol{E}_S = \boldsymbol{E}_R + \boldsymbol{E}_V + \boldsymbol{E}_D \tag{4}$$

Combining the kinetic field, potential field, and behaviour field results in the total safety field strength as shown by Equation 4.

Due to the lack of previous information on the topic, a relative safety field strength was created to analyse the collected conflict data. This relative safety field strength is shown by Equation 5. This equation is the main method for comparing the simulation data because it makes it possible to compare the safety field values even when using multiple different types of vehicles.

$$E_{R,\ i,\ t} = E_{i,\ t} - E_{i,\ F} \tag{5}$$

Where:

- $E_{R,\ i,\ t}$: Relative field strength of vehicle i and timestep t.
- $E_{i,\ t}$: Field strength of vehicle i at timestep t.
- $E_{i,\ F}$: Field strength of vehicle i at final timestep.

Table 1 and Table 2 show the most important tables of the results. Table 1 shows the number of conflicts at different thresholds of relative safety field strength, and Table 2 shows the conflicts above a threshold of 2.1 as well as the following situation for each conflict. These tables show that there are clear benefits to be gained from the introduction of CAVs into the simulation. A penetration rate (percentage of CAVs on the road section) of 65% leads to the least number of conflicts, but this is partly caused because such a large range of conflict severity is taken into account. When only looking at a safety field strength of 2.1 or above, the highest penetration rates also have the fewest conflicts. This can be explained by the lack of conflicts that occur in the following situation of CAV following an HDV (Human Driven Vehicle). The cautious nature of CAVs when they follow a human driver ensures that they do not get into the critical conflict range.

Table 1: Number of conflicts per conflict severity and penetration

Conflict Severity	**0**	**10**	**20**	**30**	**35**	**40**	**45**	**50**	**55**	**60**	**65**	**70**	**80**	**90**	**100**
1-1.5	5682	6147	6392	6636	6748	6841	6928	6949	6940	6879	6915	6818	6852	6429	6189
1.5-1.8	3159	3169	2953	2795	2766	2702	2736	2783	2847	2902	2994	3142	3556	3860	4481
1.8-2.1	3250	3159	3159	3135	3197	3169	3201	3340	3441	3663	3861	4192	4853	5439	6192
>2.1	8433	7260	6206	5406	5076	4769	4327	3862	3521	3172	2762	2466	1699	1201	661
Total	20524	19735	18709	17972	17787	17482	17192	16934	16749	16616	16531	16618	16960	16929	17523

Table 2: Relative safety field strength >2.1 conflict types per penetration

Threshold >2.1	**0**	**10**	**20**	**30**	**35**	**40**	**45**	**50**	**55**	**60**	**65**	**70**	**80**	**90**	**100**
HDV-HDV	8433	6535	4986	3745	3321	2790	2281	1827	1457	1174	875	703	239	52	0
HDV-CAV	0	700	1163	1578	1646	1825	1872	1846	1821	1722	1644	1452	1076	620	0
CAV-CAV	0	25	57	84	110	154	175	190	244	276	242	312	384	529	661
CAV-HDV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	8433	7260	6206	5406	5076	4769	4327	3862	3521	3172	2762	2466	1699	1201	661

On top of these results, a sensitivity analysis was performed to determine the effects of several input variables. Here the maximum acceleration, maximum deceleration, driving risk parameter, and disturbance velocity were tested. Varying the maximum deceleration yielded unexpected results, instead of increasing the number of conflicts, reducing the maximum deceleration resulted in fewer conflicts. The milder style of driving benefited the simulation results as they were less likely to cause a conflict when braking hard. For maximum acceleration, the number of conflicts increased with the maximum acceleration, but these changes were quite mild. The changes made to disturbance velocity and driving risk were more significant. Increasing the driving risk heavily affected the number of conflicts and showed that in situations with a lot of risky driving happening, that CAVs would be even better able to solve potential conflicts on that road system. Changing the disturbance velocity also changed the number of conflicts heavily. Here the slopes per penetration rate were not necessarily affected, but the number of conflicts would increase or decrease by a certain margin. The slower the vehicles would have to drive, the more conflicts occurred.

Both the literature review as well as the simulation results showed that traffic safety is positively influenced by the introduction of CAVs onto the road. The literature review showed that it was possible to translate herd immunity for viruses to herd immunity for car traffic. The mechanisms in either are similar and possible to be translated. The impact assessment showed that not only do the number of conflicts decrease as the penetration rate increases, it also decreases the severity of these conflicts. At a 100% penetration rate, CAVs following other CAVs caused so few conflicts that the secondary effects of herd immunity are definitely displayed. Returning to the research question: "How is traffic safety influenced by connected (automated) vehicles considering the concept of herd immunity?" the results show that the principle of herd immunity can definitely be applied to car traffic including CAVs. These results should prove the concept, but there were some limitations in the research as well. The main limitations were due to the limited comparison material. No previous research was done on this topic and it makes it difficult to compare to any existing data. On top of that, the safety metric of safety fields is still being developed and has seen limited use. Equation 5 was created specially for this research and has potential in the future to help other researchers to be able to compare the the values of the safety field strength. The lack of other research with safety fields did make it difficult to determine the proper calibration values. The limitations do not reduce the quality of the results, but it shows that there is sufficient additional research to be performed on this topic. The recommendations are based on expanding the research done with this research as prior knowledge. Especially safety fields has the potential to become an effective safety metric because it provides so much more information than any other safety metric. The inclusion of the behavioural field and the static field adds to the effectiveness of this safety metric. Additional scenarios would also help support this research, because if the concept can be proved for other scenarios, then CAVs have that much more reason to be developed.

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1
Introduction

Connected Automated Vehicles (CAVs) are an emerging topic in the field of transportation. These vehicles are able to communicate with other connected vehicles or surrounding infrastructure to share information. The information shared can be anywhere from individual car actions to traffic data. For the rest of this paper, CAVs concern levels 4 and 5 of the SAE levels of vehicle automation. CAVs come with a plethora of advantages ranging from fewer crashes, to better traffic flow due to smaller headways and faster reaction times (Fagnant and Kockelman [2], 2015). Although this might not seem like a big deal, the yearly crashes and subsequent fatalities and injuries are still far too high. Not only that, but CAVs can make driving more efficient as they are better able of keeping ideal speeds to reduce fuel expenditure. This master's thesis focuses on the safety impacts that CAVs can have on the surrounding vehicles through the concept of herd immunity. Herd immunity is a concept that is used to describe the spread of a virus when members of the population start being immunised for the virus. How the concept connects to CAVs is that the CAVs can be considered the immunised members of the population. Through this, it is surmised that the safety of all vehicles on the road improves due to the introduction of CAVs. This thesis looks to explore this concept through a literature review and through modelling scenarios where CAVs are present. The literature review focuses on the types of car-following models and the traffic safety of CAVs. The model itself makes use of car-following models and metrics of safety to determine the safety of the scenarios.

1.1. Problem Analysis

There are a number of important topics to discuss in the problem analysis. Firstly, herd immunity has not previously been used while modelling vehicles. This provides scientific relevance to the topic as it is a concept not discussed previously. Therefore, the mechanism of how herd immunity functions needs to be researched. Figure 1.1 shows how herd immunity works in a population. As more members of the population are immunised, viral spread is reduced. In the case of vehicle traffic, the immunised vehicles would be the CAVs. The CAVs are theorised to improve the safety of all surrounding vehicles. This concept is based on the idea that CAVs can absorb errors made by the HDVs (human driven vehicles). Fagnant and Kockelman [2] (2015) claim that 93% of all crashes are due to human error. The same papers goes on to describe that CAVs have a number of aspects that humans cannot replicate:

- CAVs have an improved situational awareness through potential wireless communication with infrastructure or other connected vehicles.
- CAVs have a faster reaction time close to 0 seconds.
- CAVs can check all their surroundings simultaneously.

Through the above points, CAVs are able to improve the stability of a road. The improved stability stems from smoother braking and fine speed adjustments (Fagnant and Kockelman [2], 2015). This reduces the turbulence that occurs on a highway and improve the traffic flow, while also improving the road safety.

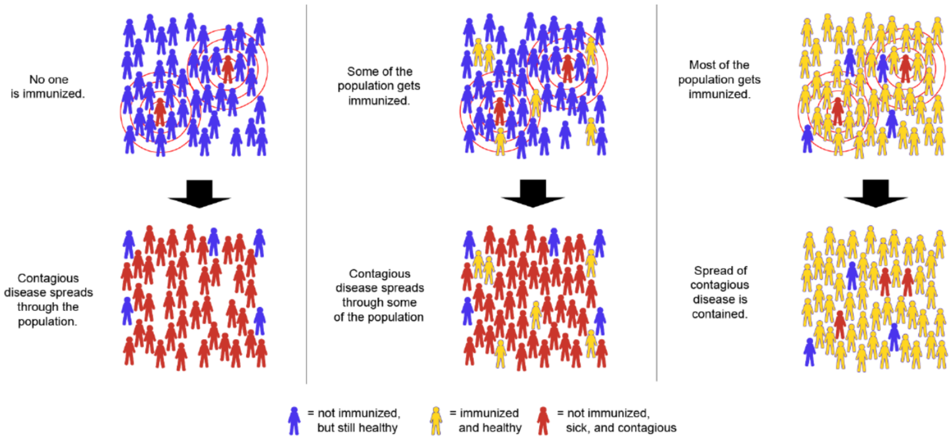

Figure 1.1: Herd immunity

To compare herd immunity in organisms to herd immunity in CAVs it is necessary to look at how a virus spreads. The core principles of how a virus spreads can be translated to herd immunity for cars. Gao *et al.* [3] (2021), Arav *et al.* [4] (2020), and Bouchnita and Jebrane [5] (2020) have all done work in describing how a virus spreads. The papers also go on to create node models to mathematically describe the spread of the virus. Vehicles on a road are bound to act differently than a virus in a population, but the effects of immunised members can be similar. This is why the comparison can be made. This similarity is depicted by Figure 1.2. By effectively nullifying mistakes made by HDVs, CAVs can improve the safety of all surrounding vehicles. Previous studies have corroborated the idea that CAVs can improve the safety of a road, but not in the manner proposed in this paper.

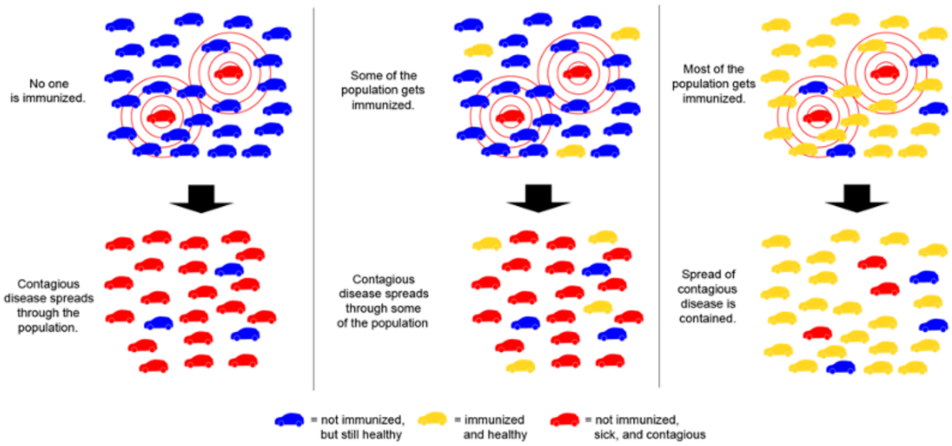

Figure 1.2: CAV Herd immunity

With the above concept in mind, MATLAB is used as a tool to simulate CAVs and HDVs to explore the concept of herd immunity for car traffic. This is done in combination with metrics of safety to be able to measure the level of safety of the simulated scenarios. There are a number of components necessary to create this model. First, the scenarios have to be chosen. In order to prove the concept, scenarios are used that are simple by nature such as, a single lane road. This decision was made because proving the concept of herd immunity is the main objective of this research and adding unnecessary complexities could affect the quality of that research. The driving process is dynamic by itself and making it more complex could make it more difficult to capture the effect of herd immunity. The car-following model used should follow a similar structure. It should be simple to understand and use for small scale scenarios.

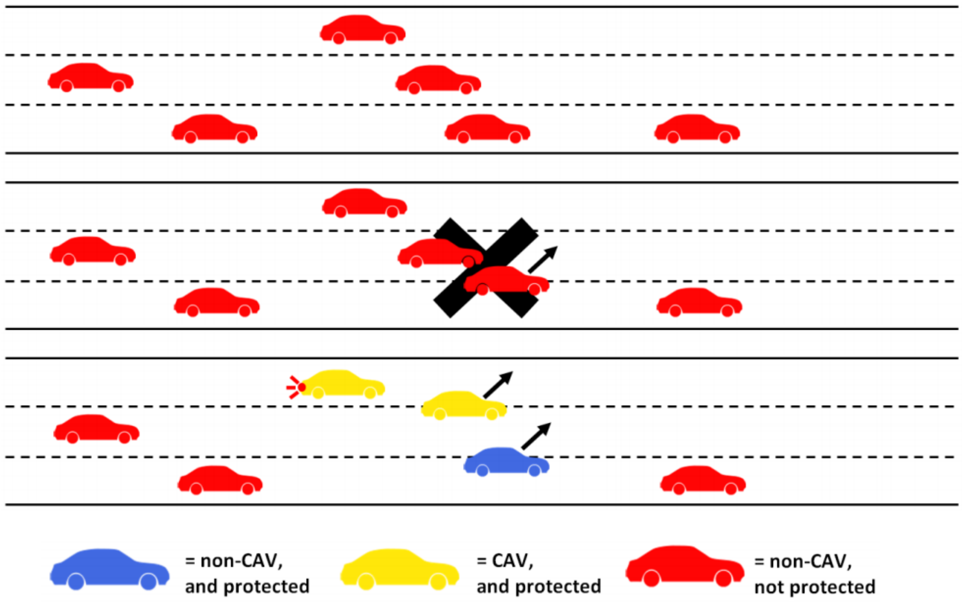

Figure 1.3: Blind spot interaction

Figure 1.3 depicts a vehicle crash due to lane-changing in a blind spot. CAVs could react to manoeuvres quickly and make the necessary adjustments to stop an accident from happening. Additionally, by contacting surrounding vehicles, they could let the rest of the vehicles on the road know that they had to change their path. This is just one of the few ways in which CAVs could absorb the mistakes made by another driver and compensate for that behaviour by contacting other connected vehicles to notify that turbulence will occur. This leads to following vehicles reducing their speed and also reduces the need for hard braking. Another common road crash is a rear-end collision. Staver [6] (2020) claims that rear-end collisions are the most common type of crashes between two vehicles. Using the concept of herd immunity, connected vehicles could let upstream vehicles know that there is congestion ahead. By letting the upstream vehicles know this, they can start reducing their speeds to make all vehicles start reducing their speed, significantly lowering the chances of a rear-end collision. These are just two examples of how the concept of herd immunity can apply to vehicles on a highway. The above statements are all possible scenarios, but the concept has to be proven in a simulation.

Determining the safety of each scenario is key to this research as there are many possible methods to apply. There is no historical crash data available because SAE levels 4 or 5 vehicles have not been created yet. Therefore, it is necessary to rely on other methods to determine the safety of a road. Many studies in the past (Huang *et al.* [7], 2013, Vogel [8], 2003, Sayed *et al.* [9], 1994, Meng and Qu [10], 2012, and others) have made use of metrics of safety to quantify the safety of a road. This is done through counting the number of conflicts that occur during the simulations. These studies provide reasoning for which metrics of safety are appropriate for each type of scenario. In Chapter 2 the literature review is performed in which the safety metrics are described in their definitions as well as their advantages and limitations.

Traffic safety is not the only topic in the literature review. More decisions have to be made regarding the model. One of the aspects of the model is the driving behaviour of the HDVs and CAVs. For the concept of herd immunity, it is important that the driving behaviour of HDVs and CAVs sufficiently differs. This can be done using a microscopic car-following model in which the parameters change depending on the type of vehicle.

For road traffic, a general definition of risk is defined by Papadimitriou *et al.* [11] (2013): "A risk is the expected road safety outcome, given a certain exposure (i.e. per unit of exposure)." More definitions of risk are available in the paper, but all of these define risk as having a unit of measurement. For the purpose of this research, **crash risk** is an inherent property of a group of vehicles on a road, that refers to the probability that a crash would occur at a certain point in time. Crash risk is the term that is related to the risk of infection that is used when considering a virus. The term crash risk is used in the research to compare the concept of herd immunity for cars to the concept of herd immunity for viruses by relating crash risk to risk of viral infection.

1.2. PROBLEM STATEMENT

The problem statement for this master's thesis reads: "Connected Automated Vehicles are an emerging topic in the transport sector. Research should be done and models must be created to determine how this innovation affects the safety of the road because it can result in positive change in traffic safety. The existing principle of herd immunity is theorised to also be able to take effect on CAVs where the CAVs act like immunised members of the population. The principle requires an impact assessment to determine the extent at which the road becomes safer."

1.3. RESEARCH QUESTION

This section is used to name all the research questions that are answered in the rest of the project. The section is important because it helps aim the project. The conclusion in Chapter 6 answers each of these questions.

Combining the problem analysis with the problem statement leads to the following research question:

How is traffic safety influenced by connected (automated) vehicles considering the concept of herd immunity?

To be able to answer this question, a number of subquestions must be answered before being able to answer the main research question.

1. What are the differences between the driving behaviour of a CAV and an HDV?
2. What are the core principles of herd immunity and how can it be translated to traffic simulation?
3. Which car-following and lane-change model is most appropriate to model CAVs?
4. Which tactical manoeuvres should be implemented into the model?
5. What are suitable safety metrics for traffic simulation using CAVs?
6. At which penetration rates is there a significant difference in traffic safety due to the herd immunity phenomenon?

The subquestions above are partly answered in the literature review and partly answered using the model. The model uses a car-following model, a lane change model, and metric(s) of safety. These are discussed in the following literature review. Each subquestion serves the purpose of filling in a part of the model. The driving behaviour differences are used to distinguish the values of parameters between CAVs and HDVs. The core principles of herd immunity are translated to car traffic to draw parallels between the concepts. The car-following model and lane-change model provide the movement of the following vehicles and as such determine the distances between vehicles. This is important for the safety metrics that determine how many conflicts occur during the car-following procedure. The last subquestion is answered in part by the literature review as previous research has been done to determine at what penetration of CAVs the overall traffic safety improves. To ensure that the literature review is properly performed, Section 1.5 is a short methodology to describe how the literature review is performed.

1.4. SCOPE

This section describes the scope of the project. Everything that is included or excluded regarding the research project is mentioned here.

As mentioned in the problem analysis, this project is focused on proving the concept of herd immunity for an environment in which CAVs and HDVs are used. The necessary topics of research are herd immunity, car-following models, lane-change models, and traffic safety. The theory behind each of these topics is discussed in Chapter 2. The purpose for researching each of these topics is to be able to make decisions regarding the simulation model. These decisions shape the model to make it best suited for simulating CAVs.

Herd immunity describes how a group of people or a population can become resistant to a virus due to immunisations. Determining how a virus spreads can give insight on how the safety of a road can be influenced by CAVs. The mechanism of how a virus spreads can be dependent on a number of factors like distance, age, and population density. These factors can be translated to how crash risk can spread in car traffic. The virus in this research is related to road turbulence that can occur in traffic. Turbulence on a freeway is defined by the individual changes in speed, headways, and lanes on the road, regardless of the cause of the changes (van Beinum [12], 2018). Each of these factors determines how the virus in the road spreads, where the virus is the inherent crash risk of a traffic system. For scoping purposes, translating herd immunity of viruses to that of cars is done through the literature review, and an impact assessment is done using the simulation model. The simulation model looks at the extent of the safety benefits that CAVs can provide rather than the theory of herd immunity for car traffic.

The scenario has a number of requirements. Firstly the model only includes one lane. The single lane scenario is used to demonstrate that the concept of herd immunity could prove to have merit. This is not to prove that the concept works for all scenarios, but rather for this single situation, which could lead to it being tested for additional situations. This is reliant on the single lane scenario proving that it is possible to apply the concept to such a situation. The scenario makes use of CAVs. This is necessary because the idea is that the CAVs will emulate the immunised members of the population. This means that the levels of automation 4 and 5 are implemented. Connected Vehicles (CVs) will not be held in consideration because a human would be responsible for vehicle manoeuvres which results in a third set of driver behaviour. This would increase the scenario complexity which is not necessary for the purpose of answering the research question. By using CAVs, it is ensured that they follow the recommendations of other upstream CAVs when there is congestion downstream. These recommendations could be to reduce speeds to limit the flow into the congested area, and reduce the chances of a rear-end collision.

To ensure that the project is feasible within the allotted time it is necessary to introduce some boundaries onto the research. This holds true especially for the different types of models that are available. Car-following models as well as lane-change models are a popular topic and a lot of research has been done on it. The model starts off small scale, therefore it is necessary to use microscopic car-following models. All macroscopic models are ignored for the duration of this research. To further scope the project, the car-following models must be appropriate for freeway situations. Signalised intersections will not be used because it would make the model more complex and introduce more possible conflicts. Added complexities do not serve to prove the concept of herd immunity. Similarly, the lane-change models that are considered should be appropriate for highway situations. Macroscopic lane-change models will also be left out of consideration. Primarily the model only considers a single lane situation. So a lane-change model is not necessary in the original scenario.

To measure safety in the model, it is necessary to quantify safety. This can be done through the use of safety metrics. These metrics of safety count the number of conflicts that occur. This makes it possible to compare scenarios with one another because the number of conflicts changes. This is especially important for when the penetration rate of CAVs changes. This is the main method of measuring the safety of each scenario because crash data is not available on vehicles that do not exist yet. In a single lane scenario, rear-end collisions are the only type of collisions that can occur during simulation. This information is necessary for determining which of the safety metrics is used during simulations.

The simulations take place as the second part of this thesis. First, a literature review is performed in which all the driving behaviour parameters for both CAVs and HDVs is determined. Additionally, the car-following model, lane-changing model, and appropriate metrics of safety are chosen to best fit the scenario. The literature review focuses on these decisions. The research includes previous research done by others to review the effectiveness of the models chosen for each scenario that it has been chosen for.

1.5. Literature Study Methodology

The literature study is an important section of the paper. It provides the background information necessary to create the model. Each of the decisions made in the literature study make up parts of the model.

The literature study is split into three sections:

1. Herd Immunity
2. Traffic Safety
3. Traffic Simulation

The herd immunity section provides information about how herd immunity functions. It is not possible to translate the principles of herd immunity directly to traffic safety because the concepts that make up the quantifiable danger are incomparable. The purpose of this section is to discover the important factors that make up the mechanism of a virus spreading. This could be factors such as frequency for washing hands, population density, and average proximity to another person. These factors could translate to factors of traffic safety like vehicle speeds, average headway, and reaction time, which are all a part of road turbulence. Discovering how these factors could be related to one another is the main purpose of the first section. Other than that, it provides a background for how herd immunity works, as well as its definition.

The strategy for researching traffic safety depends on safety metrics. Safety metrics need to be used because simulating crashes is not possible. In some types of software crashes or extreme congestion cause vehicles to disappear to allow the simulation to continue. In other cases the vehicles overlap because the vehicles do not contain any mass or area and the simulation would continue simply because it does not recognize the situation as a crash. In simulations, quantifying safety relies on the conflicts that can be counted using metrics of safety. The metrics of safety have to fit a number of requirements. The chosen metric of safety needs to function for a single or double lane highway situation. Additionally, past research papers are compared to determine when each metric of safety was effective. Another overview is created to make a comparison of all the types of safety metrics. Additionally, a conceptual framework is necessary to be able to compare the mechanics of virus transfer to the mechanics of crash risk transfer. This provides an overview to compare the two concepts effectively.

The traffic simulation section of the literature review is primarily focused on car-following models, driving behaviour, and lane change models, and to see which models and behaviours are the most appropriate for the purpose of this paper.

Therefore, for car-following models, an overview is created that compares these models. The overview looks at the types of car-following model as well as papers that have used them in the past. Most importantly, the car-following models must fit a number of criteria. Namely: they must be microscopic car-following models, appropriate for highway scenarios, and have the option to allow for CAV behaviour. Papers that used the models in the past are reviewed and compared to others to find the best possible model for this project. Following this, the next section is the driving behaviour. The topics of the car-following model and driving behaviour tie in well together because the car-following model needs to encompass HDV behaviour as well as CAV behaviour. This is done through the change in the parameters. These parameters can be reaction times, headway, and more, but what is important is that the car-following model can appropriately model both.

The lane-change model is similar to the car-following model in that an overview is created to compare the models. These models follow the same criteria as the car-following models in that they need to be microscopic as well as having the ability to model CAVs. The strategy for researching these models is by comparing papers that have used such models previously. The lane-change models combined with the car-following model will make up the vehicle dynamics. Although all types of lane-change models are considered, some are more suitable in a designated software like VISSIM. The Wiedemann driving behaviour model is the default for VISSIM.

1.6. Report Structure

The report is set up in the following manner: Chapter 2 is the literature review where most of the research is presented and decisions about the model are being made. Chapter 3 is the methodology where the plan for simulations is described. After this in Chapter 4 the simulation results are presented. These results are discussed in Chapter 5. Finally Chapter 6 provides the conclusions and recommendations.

2

Literature Review

This chapter presents the findings from the literature with a review in each section to describe the choices made.

2.1. Herd Immunity

This section is used to describe what herd immunity is, both in definition as well as how it is relevant to this project. This section looks at how a virus spreads to try and describe how unsafe situations can occur in traffic. These situations can range anywhere from rear-end collisions to missing a vehicle in the blind spot. Most of these situations occur due to turbulence on the road which can be caused by any number of things, which is discussed in this section.

2.1.1. Definition

The definition of herd immunity is different between papers. One paper (John and Samuel [13] 2000) found three leading definitions of it.

1. "The resistance of a group to attack by a disease because of the immunity of a large proportion of the members and consequent lessening of the likelihood of an affected individual coming into contact with a susceptible individual."
2. "It is not necessary to immunise every person in order to stop transmission of an infectious agent through a population. For those organisms dependent upon person-to-person transmission, there my be a definable prevalence of immunity in the population above which it becomes difficult for the organism to circulate and reach new susceptibles. This prevalence is called herd immunity."
3. "It is well known that not everyone in a population needs to be immunised to eliminate disease - often referred to as herd immunity. This is because successful immunisation reduces the number of susceptibles in the population and this effectively reduces the efficiency with with the microbe is transmitted from one person to the other. This has the same effect on the incidence of infection as a reduction in the number of individuals in a population. The microbe cannot sustain itself and the disease disappears at some level of vaccine coverage that is less than 100%..."

The third definition continues longer but is not relevant for the actual meaning of the concept. The first definition is the most straightforward and also most relevant to this paper. The immunised members of the population have a resistance to the virus. This translates to CAVs as the virus being the unsafe situations that can occur in traffic. The CAVs are hypothesized to alleviate the risk that is inherent in any traffic scenario. Not only with direct impacts, but also indirectly improving the safety of the entire road by absorbing the mistakes made by human drivers. In the following sections the relation between virus spread and unsafe scenarios in traffic is explained.

2.1.2. Virus Spreading Mechanism

This subsection focuses on the manner in which a virus spreads. Arav *et al.* [4] (2020) claims that respiratory viruses generally spread through three different ways; contact, droplet, and aerosol. Contact encompasses everything from shaking someone's hand to touching an object that an infected person has transferred the virus to. Droplets can spread the virus when an infected person coughs or sneezes. These droplets can travel 1.5 meters and then stick to surfaces. Finally the virus can spread through aerosol by being suspended in the air and then breathed by non-infected people walking through it. To help prevent the spread of a virus there are a number of methods. This is done through cleaning hands and furniture more thoroughly. These methods can be seen in Figure 2.1.

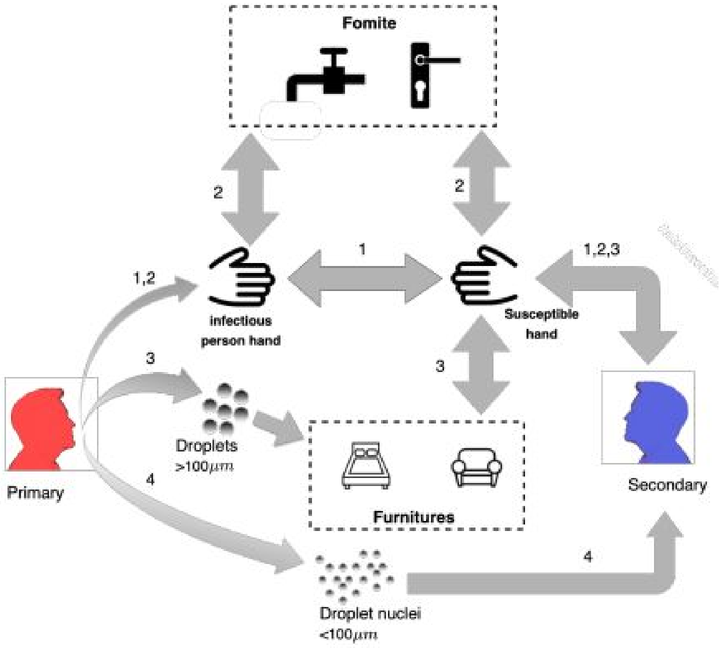

Figure 2.1: How a virus spreads according to Arav *et al.* [4] (2020)

A different study (Gao *et al.* [3], 2021) includes another method in which a virus can spread. This is through long-range airborne transmission. This can happen due to an airflow within a space. This is depicted by Figure 2.2. Ventilation in a room can cause the virus to spread throughout the room even if people remain distant from one another. Gao *et al.* [3] (2021) also proceeds to create a multi-route transmission model. This describes the total risk that an individual would have when visiting a location.

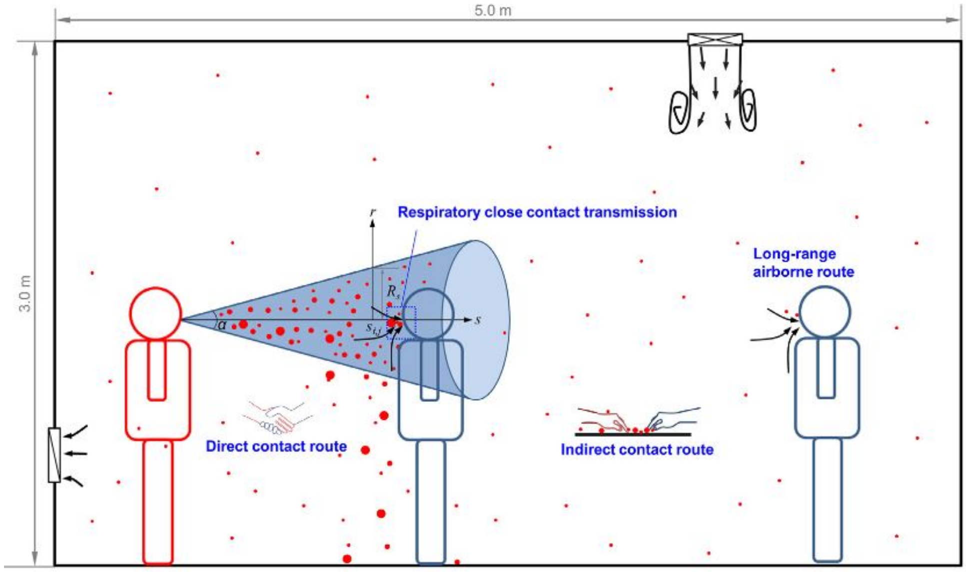

Figure 2.2: How a virus spreads according to Gao *et al.* [3] (2021)

The transmission models in the paper by Gao *et al.* [3] (2021) differ depending on the type of exposure to a virus. The total infection that an individual can be exposed to is dependent on the different types of exposure. The infection risk is therefore given by Equation 2.1.

$$P_i^k = 1 - e^{-\left(\eta_a \mathrm{D}_{in}^k + \eta_{la} D_{sa}^k + \eta_{\mathrm{lin}} D_{in}^k + \eta_m D_d^k + \eta_m D_{hs}^k + \eta_m D_{hh}^k\right)} \tag{2.1}$$

$D_{la}^k, D_{sa}^k, D_{in,}^k D_d^k$ are the factors that denote the different types of long range exposure. D_{hs}^k and D_{hh}^k are the factors that denote the exposure due to contact with a contaminated surface or direct hand to hand contact. Each of these types of exposure are dependent on factors such as humidity, distance, droplet size, and even the spreading angle of the cough or sneeze. The specifics of each of these models is not relevant for this paper but it does provide insight on which factors have an impact on the risk of infection.

Another model was created by Bouchnita and Jebrane [5] (2020) which uses an area of 250 m^2 where agents are introduced who could all potentially be symptomatic of a virus (in this the SARS-CoV-2 virus). The paper wants to simulate the transmission dynamics of such a virus. This is done by making the agents move in random directions to reach their destination. The model takes into account the distance that two agents would want to keep between one another. This is done using a force model depicted below by Equation 2.2.

$$f_i^{\mathrm{self}} = m_i \frac{v_{d,i} - v_i}{\tau_i} \tag{2.2}$$

This equation shows the driving force behind each agent. It makes use of an agent's mass, desired velocity, and relaxation time. The relaxation time depicts how long an agent takes to recover its velocity after its path has been hindered. Although the model is focused on pedestrian dynamics, it can be relevant for cars as well. The way the virus is transmitted is through close contact of the agents, this is also how conflicts can occur with vehicles. The chance of being infected can be translated to the chances that a crash would occur. In regards to simulations, it would have to be translated to the number of conflicts that occur.

The main conclusions to be drawn from the mechanics of virus transmission is that there are a number of factors that take precedent when describing the transmission of the virus. Humidity, distance, frequency of hand washing, and droplet size are factors that can influence the transmission. How this relates to vehicles is that similar factors can affect traffic safety; average headway, average vehicle speeds, weather, reaction times, and traffic volume to name a few. In the context of traffic safety simulation, the number of conflicts identified by the metric of safety will be influenced.

2.2. Traffic Safety

This section reviews possible safety metrics used for car traffic, whether it be simulations or simply observing traffic in real time. The purpose of this section is to determine how CAVs can have an impact on which safety metric should be used in each scenario as well as considering an appropriate metric for the simulation model.

2.2.1. Safety Metric Review

To be able to measure the safety of the simulations, a review of the safety metrics is done. In this review their suitability for different scenarios is discussed. Certain safety metrics are more suitable than others for simulations and the types of possible collisions that can occur. The most common type of collision to occur while driving is a rear-end collision. This type of collision is in the longitudinal direction instead of the lateral direction. Different safety metrics are necessary for the two directions. Mahmud *et al.* [14] (2017) provides an overview of the many safety metrics that can be used for measuring safety. Each of these metrics uses different methods to measure safety. Table 2.1 and Table 2.2 provide an overview for each type of safety metric that can be used, and what their limitations and advantages are. These tables make use of the papers by Mahmud *et al.* [14], Papadoulis *et al.* [15] (2019), Åsljung *et al.* [16] (2016), Ye and Yamamoto [17] (2019), Wang *et al.* [1] (2015), and Mullakkal-Babu *et al.* [18] (2020).

Table 2.1: Safety metric comparison part 1

Metrics of safety	Type of indicator	Definition	Limitations	Advantages
Time to collision (TTC) (seconds)	Temporal proximal indicator	Time till collision between two vehicles if they follow their current trajectories.	Consecutive vehicles keep constant speeds. Ignore many potential conflicts due to acceleration or deceleration discrepancies. Can provide magnitude for crashes but not the severity. Collision course must exist. TTC index cannot be calculated if leading vehicle is faster than following vehicle.	TTC is more informative than PET. Many collision avoidance systems or driver assistance systems have used TTC as an important warning criterion. Applicable for work zone safety analysis. Applicable in post-processor such as SSAM.
Time exposed time-to-collision (TET) (seconds)	Temporal proximal indicator	Summation of all the moments that a driver approaching another vehicle with a TTC-value below the threshold value of TTC.	Does not provide variation severity levels of different TTC values below the threshold value. If TTC-value is lower than threshold value, then it does not affect the TET indicator value. Data intensive.	Can be calculated separately for per user class. Can be applied in the comparison of a do-nothing case with an adapted situation. Suited for application in microscopic simulation studies of traffic. Easy to include small TTC value due to including of time-dependent TTC values of all subjects.
Time integrated Time-to-Collision (TIT) (seconds)	Temporal proximal indicator	Integral of the TTC-profile during the time that it is below the threshold.	Difficult to interpret the meaning for complexity to determine. Not preferable to use in comparative studies in which simulation tools are aplied to generate trajectories. Benefits is small due to uncertainties in driver behaviour.	Level of safety of collision can be derived. Can be applied in the comparison of a do-nothing case with an adapted situation. Suitable for microscopic simulation studies of traffic. Easy to include small TTC value due to including of time-dependent TTC values of all subjects.
Modified TTC (MTTC) (seconds)	Temporal proximal indicator	Modified model which consider all potential longitudinal conflicts due to acceleration/deceleration discrepancies.	Obtaining field speed of both users and distance gap in an evolution process is difficult and relies on other approaches. Not fit for lane-changing. Does not reflect severity of collision.	More advanced than TTC. Considers driver discrepancies. Severity of the collision could be weighted using CI indicators.
Crash Index (CI)	Temporal proximal indicator	The influence of speed on kinetic energy for collisions.	Describes only the safety information about two vehicles at a certain time and place. Not fit for lane-changing or head-on collision.	Reflect the severity of a potential crash. Describes the influence of speed on kinetic energy involved in collisions. Consider the elapsed-time before the conflict occurred. Severity and the likelihood of a potential conflict could be interpreted.
Time-to-Accident (TA) (seconds)	Temporal proximal indicator	The time it takes from the moment that one driver starts taking an evasive action until the crash that would have happened if same trajectory was used.	Often criticised for relying heavily on the subjective judgement of speed and distance. Mainly rely on the evasive action.	Widely used. Easy to measure. Can be done by both manually or by video analysis. Couple of manuals have been developed in different countries.
Post-Encroachment time (PET) (seconds)	Temporal proximal indicator	The time between the moment that a driver leaves the area of a potential collision and the other user arrives at the collision area.	Only useful in the case of transversal trajectories. Cannot reflect changes with the dynamics of safety-critical events over a larger area. Levels of severity as well as impact are not taken into account.	PET is more appropriate than TTC for intersecting conflicts. PET can be easily extracted. PETs can be easily estimated using photometric analysis in video or simulated environment. PET represents the driver behaviour.

Table 2.2: Safety metric comparison part 2

Metrics of safety	Type of indicator	Definition	Limitations	Advantages
Potential Index for Collision with Urgent Deceleration (PICUD) (meters)	Distance based proximal indicator	Distance between two vehicles considered when they completely stop.	Mainly applicable in lane changing condition when leading vehicle apply emergency break. Threshold value yet to be sated up. Does not take lateral conflicts into account.	PICUD is more suitable than TTC for evaluating the danger of collision of the consecutive vehicles with similar speeds. PICUD might detect the change in traffic condition and conflicts more sensitively than TTC.
Proportion of Stopping Distance (PSD) (meters)	Distance based proximal indicator	Ratio between remaining distance to the potential point of collision and the minimum acceptable stopping distance.	Based on evasive action. PSD provide higher percentage of vehicles interaction and time exposure to conflict than TTC and DRAC, hence there is less focus on specific safety problem.	Single vehicle conflict with fixed or unfixed objects can be evaluated. Easy for observation and calculation.
Margin to Collision (MTC) (dimensionless)	Distance based proximal indicator	Ratio of the summation of the inter-vehicular distance and the stopping distance of the preceding vehicle divided by the stopping distance of the following vehicle.	Same as stopping distance. In addition, does not consider a response delay of the following vehicle. A non-dimensional parameter.	Same as stopping distance. It also provides the possibility conflict when the preceding and following vehicle at the same time decelerate abruptly.
Difference of Space distance and Stopping distance (DSS) (meters)	Distance based proximal indicator	Difference of the space and stopping distance.	Provide information on the number of unsafe vehicles but cannot consider the degree of danger as well as the danger.	The calculation formula and dangerous threshold value are simple and clear.
Time Integrated DSS (TIDSS) (meters)	Distance based proximal indicator	Total value of the time integrated value gap between DSS and the dangerous threshold value.	Mainly suitable for rear-end conflict.	Considers the degree and the duration of danger.
Unsafe Density (UD)	Distance based proximal indicator	Level of "unsafe" in the relation between two consecutive vehicles on the road for a determined simulation step.	The value of this parameter does not have a sense in itself and must be used only for comparison purposes. Fit for only rear-end collision analysis.	Gives more accurate information than typical micro-simulation outputs. Comparative study between link can be done.
Deceleration Rate to Avoid a Crash (DRAC) (m/s^2)	Deceleration based indicators	Differential speed between a following/response vehicle and its corresponding subject/lead vehicle (SV) divided by their closing time.	Fails to accurately identify the potential traffic conflict situation. Not suitable for lateral movement.	Explicitly considers the role of differential speeds and deceleration in traffic flow.
Crash Potential Index (CPI)	Deceleration based indicators	Probability that a given DRAC exceeds its maximum available deceleration rate (MADR) during a given time interval.	Not suitable for lateral movement, mainly applicable at intersection.	Address some of the issues found in DRAC like vehicle braking capability for prevailing road and traffic conditions.
Criticality Index Function (CIF)	Deceleration based indicators	Multiplication of vehicle speed with the required deceleration.	Like TTC, it considers constant speed of consecutive vehicle, further evaluation is needed using additional field data for validation.	Chance of occurrence and severity could be measured.
Safety Fields	Other	Fields that surround each object and exert a force on their surroundings.	Lots of information is necessary for safety fields to function. Not only the vehicle information but also the information of road conditions, nonmoving objects, moving objects as well as vehicles, and driver characteristics. The difficulty to obtain this information might make the application of this model difficult. However, this could be remedied in the future as sensor technology improves and becomes commonplace in vehicles.	Compared with existing safety factors, safety fields incorporate a greater number of factors and is not limited to any one type of driving scenario. It can function on highways and on intersections. Safety fields is also highly applicable in complex scenarios, as it is one of the few safety metrics that can take all factors into account.

From the tables above a couple of safety metrics stand out as being appropriate for simulations. All types of time to collision indicators are effective for longitudinal conflicts. The advantage that these safety metrics have is that the values that are found are straightforward and simple to interpret. When a time to collision metric has a value of 2 seconds, it is clear that a collision would occur if both drivers resume their current speeds and trajectories. The main disadvantage is that these metrics are only useful in the longitudinal direction. Furthermore, the severity of a conflict can not be defined using these metrics. Using headways as a metric of safety can provide more information on the severity of the conflict simply by their distance apart. These safety metrics function under the assumption that a conflict will always precede a collision Mahmud *et al.* [14] (2017). Under this assumption, the term **crash risk** is used to describe the level of safety of the road and the number and severity of conflicts is what affects the crash risk. This assumption is important for traffic simulation regarding car-following models because crashes are not simulated. The term crash risk could be confusing due to the lack of crashes occurring in simulation, but functioning under the assumption that conflicts precede collisions, ensures that conflict data can be used to determine whether crash risk increases or decreases, and consequently the level of road safety. A safety metric that combines many of these aspects while also including driving behaviour is the safety metric of safety fields. Ultimately safety fields are an interesting topic to pursue due to them being a new development as well as taking the behavioural field into account. Therefore, more focus is put onto safety fields to describe how they function as well as an added description on their advantages and limitations.

2.2.2. Safety Fields

Safety fields are a relatively new development in traffic safety. Mullakkal-Babu *et al.* [18] (2020) describes these safety fields as areas that can have an influence on the vehicles on the road. Each object on the road (cars, traffic lights, the pavement, pedestrians, etc.) have an effect on the traffic safety. The concept of the driving safety field is a physical field that includes all the influences of traffic factors on traffic safety (Wang *et al.* [1], 2015). This field is different to other physical fields like gravitational fields and electromagnetic fields because it varies over time and space. Finally, the driving safety field is made up of vectors to show the directed influences of surrounding objects and vehicles. Each of these fields can be split into three different categories as explained by Wang *et al.* [1] (2015):

1. *The potential field* is the physical field that shows the influence that static objects can have on the driving safety. The field strength is determined by non-moving objects and road conditions.
2. *The kinetic field* is the physical field that shows the influence that moving objects can have on the driving safety. The field strength is determined by the attributes and states of the moving objects and road conditions.
3. *The behaviour field* Is the physical field that is dependent on driver behaviour characteristics. The magnitude and direction of the field strength is determined by the behaviour characteristics of drivers. In this way, aggressive drivers have a larger behaviour field than the drivers who drive more conservatively.

The behavioural, kinetic, and potential field added together make up the total safety field strength, as described by Equation 2.3. Where $\boldsymbol{E}_S$ is the field strength vector of the kinetic safety field, $\boldsymbol{E}_R$ is the field strength vector of the potential field, $\boldsymbol{E}_V$ is the field strength vector of the kinetic field, and $\boldsymbol{E}_D$ is the field strength vector of the behaviour field.

$$\boldsymbol{E}_S = \boldsymbol{E}_R + \boldsymbol{E}_V + \boldsymbol{E}_D \tag{2.3}$$

To provide an idea Figure 2.3 is used to visualise the kinetic field strength.

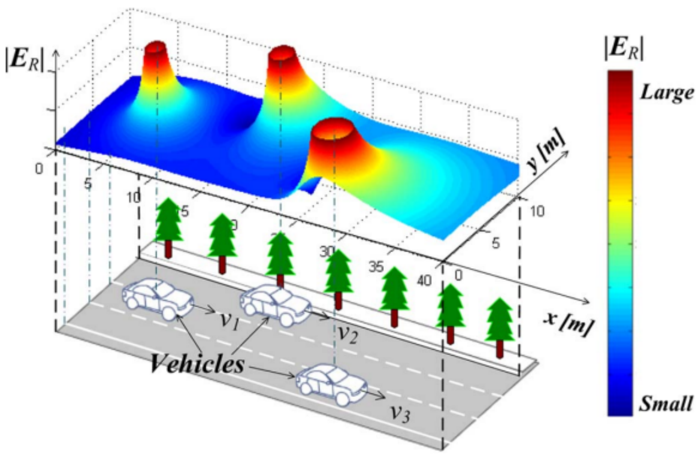

Figure 2.3: Visualisation of the kinetic field strength (Wang *et al.* [1], 2015)

The paper by Wang *et al.* [1] (2015) is based on the virtual mass of the safety field. The virtual mass of each of these fields is dependent on the attributes of the object. This is its mass, type, moving state, and speed. This is denoted by Equation 2.4. The virtual mass is necessary in order to calculate the value of the kinetic safety field strength which leads to the value of the behavioural field.

$$M_i = M_i\,(m_i, T_i, v_i) = T_i \cdot m_i \cdot \left(1 + \sum_k \alpha_k \cdot v_i^{\beta_k}\right) \tag{2.4}$$

Where:

- T_i: Vehicle type.
- m_i: Physical mass of the vehicle.
- α_k, β_k: Undetermined constants (Determined by calibration).
- v_i: Velocity of vehicle i.

The virtual mass of the vehicle is used in Equation 2.5. This equation shows how the kinetic safety field strength is calculated.

$$\boldsymbol{E}_V = \frac{G \cdot R_c \cdot M_c}{\left|\boldsymbol{r}_{cj}\right|^{k_1}} \cdot \frac{\boldsymbol{r}_{cj}}{\left|\boldsymbol{r}_{cj}\right|} \cdot e^{(k_3 v_c \cos\theta_c)} \tag{2.5}$$

Where:

- G: Gravitational constant
- R_c: Road condition influencing factor.
- M_c: Virtual mass of vehicle c.
- r_{cj}: Distance between vehicles.
- k_1 & k_3: undetermined constant greater than zero (Wang *et al.* [1], 2015).
- v_c: Velocity of vehicle c.
- θ_c: Angle between velocity of the leading vehicle and following vehicle.

The constant G is assumed to have a value of 0.001, k_1 is assumed to have a value of 1, k_3 is assumed to have a value of 0.05, and the road influencing factor R_c is set to 1 as to have no influence. The virtual mass of the vehicle can be calculated by Equation 2.4 and the distance between the vehicles is what can vary on both the road and in a simulation environment.

$\boldsymbol{E}_R$ in Equation 2.6 shows the potential safety field. It uses many aspects determined previously, except the virtual mass of the vehicle will be different because the object is not moving, therefore the velocity will not have an impact on its value.

$$\boldsymbol{E}_R = \frac{G \cdot R_c \cdot M_c}{|\boldsymbol{r}_{cj}|^{k_1}} \cdot \frac{\boldsymbol{r}_{cj}}{|\boldsymbol{r}_{cj}|} \tag{2.6}$$

Where:

- G: Gravitational constant
- R_c: Road condition influencing factor.
- M_c: Virtual mass of vehicle c.
- r_{cj}: Distance between vehicles.
- k_1 : Undetermined constant greater than zero (Wang *et al.* [1], 2015).

The advantages of using a safety metric like safety fields is that it provides the severity of each conflict as well as the number of conflicts. Another benefit is that safety fields include a greater number of traffic factors when considering the safety. Most other safety metrics only consider other vehicles when determining potential conflicts. Safety fields can take other objects into account like lane markings and the traffic barrier on the side of a freeway. The model is not limited to specific scenarios like car-following and lane-changing, although that is what it would be used for in this research.

The negative aspect of this model is that it is more complex than other models. This complexity means it would be more difficult to apply and also more difficult to understand. It is also a recent development and the calibration of the safety metric needs to be researched further. A benefit and a drawback of the safety metric is that it uses the driving behaviour as another possible safety field. The driving behaviour is quantified as a single value and using this system means that all human drivers have the same behaviour, which is far from realistic. It is a benefit because it does provide for a more realistic judgement of the safety of a vehicle. Mostly, the elements of safety fields show a lot of promise, but there is a limitation in the model when trying to compare vehicles that have different headways. When traffic reaches stability, the safety field strength will be solely reliant on the headway and the driving behaviour variable. Due to a set desired headway that could differ between behaviour types or vehicle types, it can be difficult to derive meaning from the safety field strength values between two or more behaviour types or vehicle types. The behaviour of the drivers is denoted by DR (**driving risk**) and a value between 0 and 1 which is multiplied by its kinetic field in order to obtain the effect. This does make it possible to obtain different driving behaviours such as; cautious behaviour, normal behaviour, and reckless behaviour. These can be denoted by different values of DR. Equation 2.7 shows the equation for calculating the impact of the behaviour field on the total safety field value.

$$\boldsymbol{E}_D = \boldsymbol{E}_V \cdot DR \tag{2.7}$$

Where:

- $\boldsymbol{E}_{D\_cj}$: Behaviour safety field strength.
- $\boldsymbol{E}_{V\_cj}$: Kinetic safety field strength.
- DR_c: Driver risk (dimensionless value between 0 and 1).

Higher values of $\boldsymbol{E}_D$ indicate higher risk for the vehicle because the total safety field strength would also increase. Very reckless drivers will have higher DR values than cautious drivers. This makes it possible to include types of human driving into the safety calculations. Perfect driving would be assumed to have a driving risk of 0. This is the value that CAVs use for the purpose of this research. For humans a value of 0.4 is used to denote standard driving skills (Wang *et al.* [1], 2015). This value will be used for calibration purposes but still prone to change for the final results.

Safety fields provide a dimensionless value which denotes the safety field strength at a certain point in time, using distance and velocity as the varying terms. Depending on the vehicle type, the total field strength will change due to the differences in the variable driving risk. The value of the total safety field strength does not provide any meaning. It is simply used to compare the safety between scenarios. When varying the inputs of the simulation, it is possible to compare the values of the total safety field strength with one another, to discover whether the crash risk between scenarios increases or decreases. This crash risk is what was described in Chapter 1 as being the 'virus' that transfers between the members of the population. When one driver is forced to brake hard, the 'virus' would transfer from that driver to the following driver. These situations can be considered a conflict. To identify the effect that this has on traffic safety, the severity of the conflicts is discussed in Chapter 3. Regardless of what safety metric is used, the exact effect on the crash risk is unknown, but by using number and severity of conflicts, it is possible to compare the different input values of the simulation to relate the safety from scenario to the other.

2.2.3. Herd Immunity for car traffic

How herd immunity functions for car traffic is similar to herd immunity for a virus. Instead of a virus, **crash risk** can be transferred between road users. Crash risk refers to the probability that a crash could occur at a certain point in time. Herd immunity for car traffic is defined as the resistance of a group of cars to crash risk in both primary and secondary conflicts. Primary conflicts are the conflicts that occur when two or more vehicles get too close together, and secondary conflicts are the conflicts that occur due to something having happened downstream. As described in Figure 2.4, CAVs would act as the immunised members of the group which would build the resistance to the virus (crash risk). CAVs are assumed to be able to absorb the mistakes made by human drivers by reacting quickly and correctly to those mistakes. Not only do CAVs improve the safety of their own driver, they would improve the safety of vehicles upstream because the mistake will not cause more conflicts to occur.

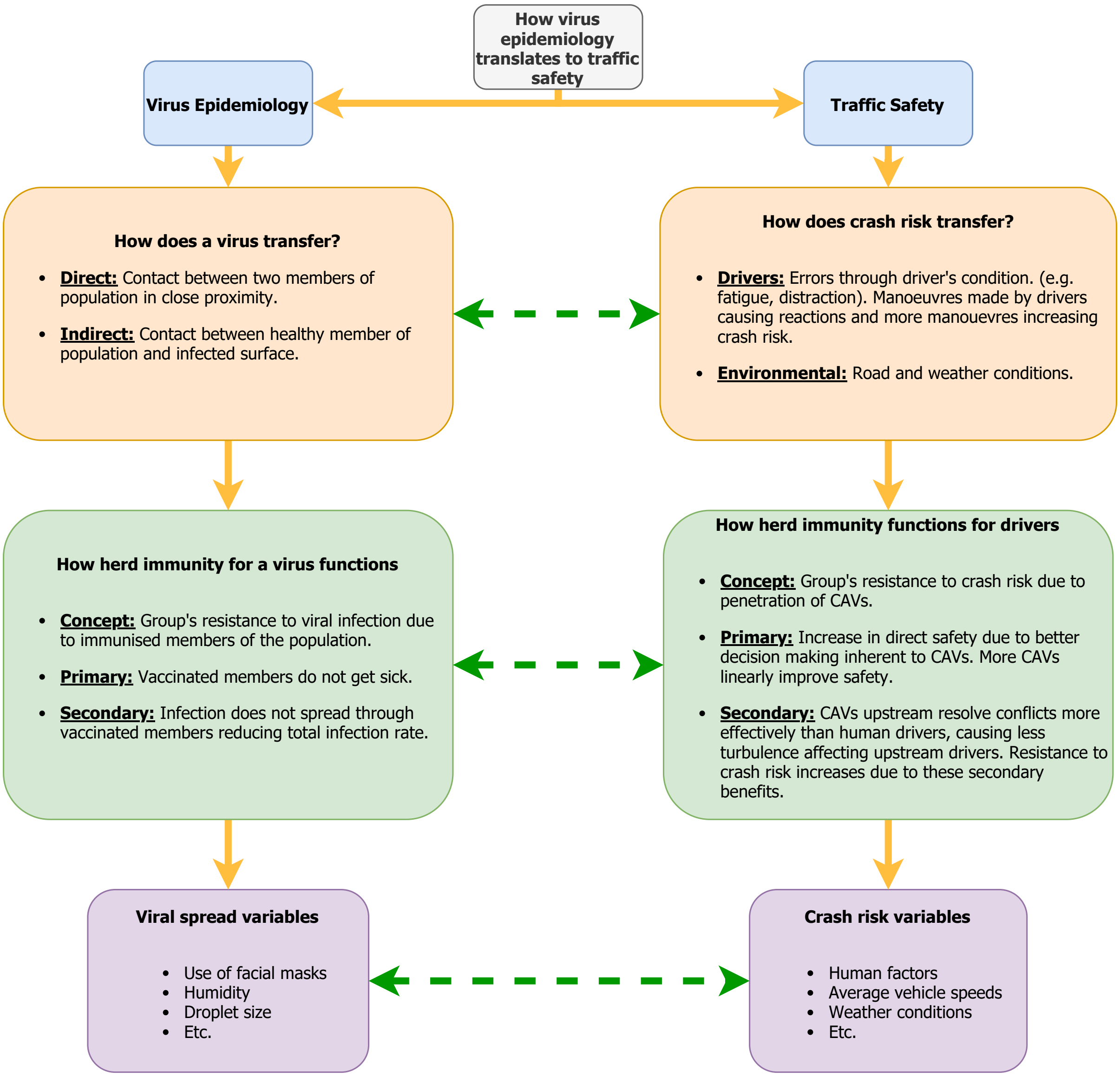

Figure 2.4: Conceptual diagram of herd immunity for car traffic

The idea behind the arrows in Figure 2.4 is that the yellow solid lines indicate a direct connection to the subsequent boxes. The green dotted lines indicate that a translation between the two objects is possible. For virus epidemiology the virus transfer can be split into two main methods, either direct or indirect. This translates to the traffic safety branch in two ways, driver transfers, and environmental transfers. These relate quite directly as direct and indirect transfer methods. Drivers can directly transfer **crash risk** (crash risk being the "virus" that spreads between vehicles) either through their state of being, or through more manoeuvres being performed. The environmental transfer is through road and weather conditions. These could impact the driver's ability to perform optimally, either due to poor visibility or other debilitating factors.

Next the concept of herd immunity is discussed for both cases. For both a virus and crash risk the concept of herd immunity is defined as the group's resistance to "infection" due to a certain percentage of immunised members or CAVs. This occurs due to the primary and secondary impacts that the immunised members provide to the population. For a virus this means that vaccinated members are less likely to show symptoms, and in turn are less contagious to the rest of the population, meaning the spread of the virus reduces in its entirety. What also occurs is a 'tipping point', where the reduction of the virus spreading is so profound that the majority of the population becomes safer due to the percentage of immunised members. For CAVs this could function similarly and this research aims to also discover whether there is a specific tipping point of a percentage of

CAVs where the safety of all drivers is improved. These secondary effects is what defines the concept of herd immunity for both crash risk and a virus.

Lastly both branches go to the variables that can have effect on the spread of a virus and on the spread of crash risk. Viral spread can be largely affected by factors relating to the environment, like the humidity, or on human factors like the use of facial masks. These can impede the spread of a virus or lack of facial masks can also cause it to spread easily. Crash risk can spread through a number of human factors, like the tendency to drive faster or slower on a stretch of highway, weather conditions, and more. These factors have to be clearly defined to determine what the impacts are of these variables.

2.3. Traffic Simulation

This section describes impacts that the driving behaviour, car-following models, and lane-change models can have on the simulation model as well as the impacts CAVs can have on the decision.

2.3.1. Driving Behaviour

This section describes the differences between the driving behaviour of a CAV and an HDV. Much research has been done previously to describe how CAVs would improve the flow of a road. The paper by Wen-Xing and Li-Dong [19] (2018) explains that in order to model CAVs, it is necessary to allow for shorter headways in the model. The paper adapts a Bando car-following model to make it more appropriate for CAVs. The paper by Zhu *et al.* [20] (2018) describes another car-following model for CAVs. According to the paper, it is necessary because there are a number of weaknesses that traditional car-following models have. The issues raised were; limited accuracy, poor generalisation capacity, and an absence of adaptive updating. The limited accuracy points towards the simple nature of most car-following models. Fewer parameters leads to a lower computational complexity and therefore faster simulations. This does decrease the accuracy of the highly complex nature of car-following. Poor generalisation capacity is due to each car-following model needing to be calibrated to the specific scenario that is being tested. Therefore, a car-following model should not be generalised to multiple traffic scenarios. Adaptive updating is also not possible with traditional car-following models. When average driver's characteristics are applied to all simulated vehicles, then it can never reflect an actual driver's behaviour as each driver is different.

The above paragraph explains some of the intricacies that can occur when modelling cars. It does not explain the specific values for certain parameters like: headway, maximum deceleration, maximum acceleration, and reaction times. To determine these parameters, previous studies are researched to determine how effectively different values have been used in the past. The study by Zhu *et al.* [20] (2018) uses a deep reinforcement learning to model car-following behaviour. The neural network model makes use of parameter inputs. In this paper they make use of relative speed, desired speed, follower speed, and gap distance as inputs to predict follower acceleration. These inputs were extracted from a data acquisition system. Using the means of this data resulted in the inputs used. Depending on the nature of the scenarios, the desired speeds would change. In the paper by Zhu *et al.* [20] (2018) the values were based on two separate types of driving behaviour, conservative and aggressive.

In a paper by Martin-Gasulla *et al.* [21] (2019) looks to improve the throughput using CAV platooning. This paper makes assumptions for the headway that are based on the Wiedemann-99 parameters that are used in VISSIM. These headway assumptions are different depending on the type of car following that is occurring. If an HDV is following an HDV or a CAV then the headway assumption is 0.9 seconds, but when a CAV is following then the value for the headway is different. When a CAV is following an HDV, there is uncertainty involved and the CAV would try to keep a distance of minimum 1.5 seconds up to and including 2.5 seconds. If a CAV is following another CAV then they allow a headway of 0.6 seconds. This is due to the communicative nature of CAVs. Instead of relying on what the sensors notice, they can communicate instantly about the manoeuvres that occur resulting in a quicker reaction from the following vehicle.

Although CAVs can communicate with one another, there is a delay in these communications. This can have an effect on the reactions of those vehicles. This should be taken into account when considering the reaction time of a CAV. Bian *et al.* [22] (2019) used simulations to determine the effects of slower communication. The reason this is taken into consideration is because reaction time is another factor that can have an effect on the driving behaviour of a CAV. In theory the reaction time of a CAV is as quick as the time needed to determine what the best possible course of action is, but delay of communication has an effect on it. This reaction time is shorter than that of an HDV.

A paper by Ye and Yamamoto [17] (2019) focuses on the safety impacts that a CAV can have. The paper discusses the driving behaviour of a CAV and how it could have impact on traffic safety. This paper assumes that a CAV would have a reaction time of 0 and behaves similarly to a vehicle using adaptive cruise control when considering the acceleration of the vehicle. This paper also corroborates what Martin-Gasulla *et al.* [21] (2019) claimed. When a CAV would be following an HDV a more cautious strategy would be applied, and when a CAV follows another CAV, a much smaller headway can be used. Liu and Fan [23] (2020) provides parameters for a revised Intelligent Driver Model (IDM) where CAVs and HDVs are compared. Here, the caution described by Martin-Gasulla *et al.* [21] (2019) is also taken into account, where the time headway would be 0.6 seconds between two CAVs, and 0.9 seconds between a CAV and an HDV.

The driving behaviours of both HDVs and CAVs have to be determined for the model, but the driving behaviour parameters depend on the car-following and lane-changing models that are considered. The chosen models determine which driving parameters are used.

2.3.2. Car-Following Models

This section mentions the possible car-following models and reviews them based on previous studies making use of them. An important criteria for these models is that they have the ability to model the differences between CAVs and HDVs.

Aghabayk *et al.* [24] (2015) presents a review of many car-following models that have been used in previous research. There are classic models and artificial intelligence models. Artificial intelligence models are potentially the most complicated models to use and are reviewed to gain a better understanding of the workings of car-following models, but they are not suitable for this research because the inner workings are not clear to the modeller. Artificial intelligence models could produce a realistic driving behaviour, but since they are not transparent, they are less suited to the research. There are four main types of car-following models; stimulus response, collision avoidance, desired headway, and psychophysical. There are two types of artificial intelligence models; fuzzy logic and neural network. The differences between these types of models is the general procedure that takes place per model. Table 2.3 reviews many of the possible car-following models. They are described more later in the chapter.

Table 2.3: Review of car-following models

Car-following model	Type	Advantages	Disadvantages
GHR model [25] Hoefs; Aron [26] Linear model; Helly [27] Optimal velocity; Bando *et al.* [28] IDM; Treiber *et al.* [29] IDM +; Schakel *et al.* [30]	Stimulus response	Easy calibration, transparent models, easy to understand Adapted IDM to achieve reasonable capacity values. Apply a minimization over the free flow and the interaction terms. This changes the fundamental diagram to a triangle instead of a smoothed top.	Only appropriate for modelling a road vehicle and not for bicycles or pedestrians. The models assume that small changes in the stimulus will be noticed and that the individual drivers will react to it. This could be inconsistent with normal driving behaviour as normal drivers do not react to small changes that much. It also assumes that reaction time is the same for all drivers and it ignores the differences between drivers and vehicle types.
Pipes [31] Kometani & Sasaki [32] Gipps [33]	Collision avoidance	Has a way of calculating a safe distance threshold and when that safe distance threshold is reached, then the collision is unavoidable. So it is a first step for measuring the safety of a road using a car-following model.	These models cannot replicate real conditions in many cases because the capacity and traffic volume are underestimates. This typ of model does not consider drivers' perception so small changes will not be noticed by the following driver. This type of model does not consider heterogeneity of drivers and vehicle types.
Bullen; [34]	Desired headway	Based on a simple assumption and no method for calibration. Different drivers in different situations might follow leaders, but this model does not capture the key points of it. The model does not consider the driver's ability to perceive small changes and so, small changes will not be recognized by the following vehicle. Additionally, the model is not able to capture the different car-following behaviour of drivers in a mixed traffic stream.	

Michaels [35] Wiedemann [36] as cited in Aghabayk *et al.* [24] Espie et al. [37] as cited in Aghabayk *et al.* [24]	Psychophysical	Better able to consider a human's perception over other classical models. Like an oversensitive reaction to small changes. The calibration of these models is far more difficult compared to the classical models. These models also use a global set of thresholds to model car-following behaviour and it does not accurately replicate the differences between vehicle types.	Only consider movement in a lane, may only be appropriate for road vehicle movements but not other modes of transport. None of these models look at driving behaviour. Generally they look at the outcome of the behaviour by measuring the spacing, velocity, and acceleration of these vehicles. The models all use a single value for the model parameters which points towards them not being able to distinguish between different driving behaviours. Another assumption is that the models all use the same reaction time. Most of the models only consider two vehicles and the interaction of a queue of vehicles might not be accurate.
Kikuchi & Chakrolborty [38] McDonald, Wu, and Brackstone [39]	Fuzzy Logic		Biggest problem is to determine the fuzzy rules as usetd by a human. If the drivers' perceptions are not applied properly then the model will be unrealistic and will not predict the behaviour properly.
Hongfei et al. [40] Panwai and Dia [41]	Neural network		Can suffer from overstudy/understudy during training process. Another issue with this type of model is that the behaviour of the model is not easily explained. The neural networks could be using inputs without providing any knowledge of the internal workings. It makes it more difficult to judge the model. Also, as with many other models, this CF model only considers movement in a lane and therefore is not appropriate for other modes. Also, the model only considers 2 vehicles, and not necessarily an entire queue of vehicles.

Stimulus Response Models

These models are based on a stimulus to which the following vehicle reacts by changing their acceleration. Within this type there are many 4 models explained by Aghabayk *et al.* [24] (2015). The GHR (Gerhaz-Herman-Rothery) model, Linear model, Optimal Velocity model, and the IDM (Intelligent Driver Model). IDM and IDM+ are described below whereas the review of the other models is in Subsection A.1.1.

IDM

This model was created by Treiber *et al.* [29] (2000, as cited in Aghabayk *et al.* [24], 2015). This model is considered as a stimulus-response model but it has some safe driving in it which puts it close to the safe-distance type of car-following models. The model is represented by Equation 2.8.

$$a = a_0 \left[1 - \left(\frac{v}{v_0} \right)^{\delta} - \left(\frac{S*}{S} \right)^2 \right] \tag{2.8}$$

Here, the first part of the equation is the free acceleration. When the following vehicle gets too close to its leader, then the braking takes effect, where $S*$ is the effective minimum gap given by Equation 2.9. S is the actual gap between two vehicles. The free acceleration is given by $a_0 \left[1 - \left(\frac{v}{v_0} \right)^{\delta} \right]$.

$$S^* = S_0 + vT + \frac{v \cdot \Delta v}{2\sqrt{a_0 \cdot b}} \tag{2.9}$$

T here is the driver's desired minimum headway, S_0 is the jam distance, and b is the desired deceleration.

There is another version of the IDM which is called IDM+ (Equation 2.10. This model is different in a small way, it takes the minimum of either the free acceleration or the deceleration strategy (denoted by $1 - \left(\frac{s'(v,\Delta v)}{s} \right)^2$) instead of either having effect on the other (Schakel *et al.* [30], 2010). The reasoning behind IDM+ is that it provides a clearer difference between the two types of car-following behaviour. This shown by Figure 2.5 which compares the fundamental diagrams of IDM and IDM+. As is shown in the figure, the fundamental diagram is not smooth for IDM+ which shows the difference between the two different states of car-following.

$$\frac{dv}{dt} = a \cdot \min \left[1 - \left(\frac{v}{v_0} \right)^4, 1 - \left(\frac{s'(v, \Delta v)}{s} \right)^2 \right] \tag{2.10}$$

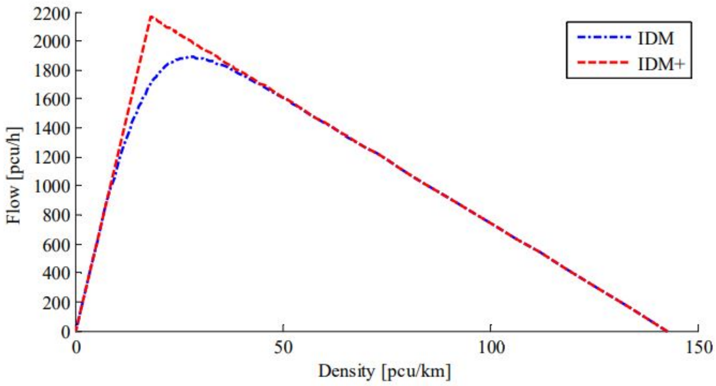

Figure 2.5: Intelligent Driver Model fundamental diagram (Schakel *et al.* [30], 2010)

Summary

Each of the stimulus-response models have advantages and disadvantages which can apply to each of them. Stimulus-response models are transparent and therefore easy to use. The equations determining acceleration as well as the calibration of each of these models is more straightforward than other models described later in this section. However there are drawbacks when applying stimulus-response models. The models can only consider movement in a single lane. This is appropriate for cars, but not for cyclists and pedestrians where overtaking is common. The models assume that drivers are able to notice subtle changes to the leader's speed when that is not the case in reality. Additionally, the models take only a single value for model parameters which assumes homogeneous driving behaviour when in reality driving behaviour is heterogeneous depending on the specific driver. This criticism is something that many car-following models suffer from because they assume that human driving behaviour is homogeneous. This is also true for the assumptions made for reaction time and desired headway. Each driver is assumed to have the exact same reaction time for simplicity. Most of the models also only consider two vehicles instead of a possible queue. The interaction between many vehicles on a road could differ heavily from simplifying it to two vehicles (Aghabayk *et al.* [24], 2015).

Collision Avoidance Models

Collision Avoidance models (also known as safe-distance models) follow Pipes' rule when it comes to car-following. The rule is as follows: "A good rule for following another vehicle at a safe distance is to allow yourself at least the length of a car between you and the vehicle ahead for every ten miles an hour of speed at which you are travelling." (Pipes [31], 1953) This rule is what the Collision Avoidance models are based on. In the event that the car that is being followed behaves unpredictably, then this provides sufficient distance for the following vehicle to take the necessary precautions. Two models are described in Subsection A.1.2; Kometani & Sasaki, and Gipps model.

This type of model is commercially popular but has some drawbacks. They have a strong base but cannot replicate real conditions in a few cases. Also, in reality, drivers use many more sources of information when making driving decisions, and they do not keep to the safe-distance that is calculated in these collision avoidance models. It does not take very small changes into account to which a real driver would react to (Aghabayk *et al.* [24], 2015).

Desired Headway Models

This type of model relies on the assumption that the following vehicle will keep to a certain headway between its front bumper and the rear bumper of the leader. Bullen [34] created the model called 'Pitt CF model' based on this fixed headway. The model is denoted by Equation 2.11.

$$a_n(t+T) = \frac{x_{n-1}(t) - x_n(t) - L_{n-1} - hv_n(t) - [v_n(t) - v_{n-1}(t)]\,T + \frac{1}{2}a_{n-1}(t+T)T^2}{T\left(h + \frac{1}{2}T\right)} \tag{2.11}$$

Where a_n is the acceleration of the following vehicle and a_{n-1} is the acceleration of the leader. This model is based on a simple assumption and there is no method of calibrating it. Furthermore, the model does not consider the driver's ability of recognizing small changes, and the following vehicle will react to every small change made by the leader. This does not reflect reality as drivers are typically not able to recognize minute changes Aghabayk *et al.* [24] (2015). Additionally, the model does not take different car-following behaviour into account when there is mixed traffic.

Psychophysical Models

Psychophysical models were developed based on the assumption that drivers can estimate the leading vehicle's speed and can react based on the visual angle changes that are made by the front vehicle. This type of model was originally introduced by Michaels [35] (1963). This model is described by Equation 2.12. θ denotes the visual angle changes that are made by the front vehicle. Many models have been made using this theory. The simulation program VISSIM runs using this car-following model (Wiedemann [36], 1974).

$$d\theta/dt = -w(\Delta v/\Delta x)^2 \quad (2.12)$$

The models make use of 4 different driving schemes; free driving, closing process, following process, and emergency braking. Depending on which driving scheme is being used, the behaviour of the driver and the acceleration can be estimated. The benefits of these types of models is that they are able to consider the human perception more effectively than other classical car-following models. They can overcome problems that other models run into like reacting to minute differences in a leader's speed. The drawback of this type of model is that they require extensive calibration. Also, they have the issue of not being able to replicate the difference in behaviour between vehicle types which is similarly present in stimulus-response car-following models and in desired headway models.

Artifical Intelligence Models

The models that have been described previously differ from artificial intelligence models in one key aspect, they have equations to describe the behaviour of the following driver. These equations are transparent and provide the programmer with the necessary tools to understand what happens at each time step of the simulation. Human behaviour is complex and different per driver. Artificial intelligence models attempt to predict human behaviour and are gaining popularity with computers becoming faster and more powerful over time (Aghabayk *et al.* [24], 2015). The artificial intelligence car-following models are split into the following two types: Fuzzy Logic Models and Neural Network Models.

Fuzzy Logic Models

Fuzzy logic models function on the idea that not all factors are considered when making decisions regarding driving behaviour. As a follower approaches a leader, they might decide to not consider the exact differences in speed and spacing because they base all their decisions on experience, logic, and judgements (Aghabayk *et al.* [24], 2015). Kikuchi and Chakroborty [38] (1992) were the first to use fuzzy logic for car-following behaviour. Many others have also attempted to use fuzzy logic to model car-following behaviour but one main problem persisted. Determining the fuzzy rules as used by a human is difficult. If these rules are not properly applied to the model then the model will behave unrealistically and cannot predict the drivers' behaviours properly. Another issue with the fuzzy logic models is that none of the groups that attempted to use fuzzy logic to model car-following behaviour considered traffic's heterogeneity, which is a problem that the classical models also suffered from.

Neural Network Models

Neural networks function differently from most other models as it tries to replicate the functions of a human brain in a fundamental manner. This is based on neurobiological studies and modern human brain's cognitive science (Aghabayk *et al.* [24], 2015). Neural networks were used broadly in the 1990s as driving behaviour and autonomous vehicles gained popularity as topics within the transport sector. Hongfei *et al.* [40] (2003) made use of a 'back propagation' algorithm to develop a car-following model using data collected by a technique called the 'five-wheel system'. Similarly to psychophysical models, the drivers were split into categories depending on their behaviour. Here there are three categories; risky, ordinary, and conservative. These categories are based on the observed speed. If the drivers were in the top 15 percent of speeds observed they would be classified into the 'risky' category, the lowest 15 percent were 'conservative' drivers, and everything in between were ordinary drivers. Using this information the neural network is able to predict the acceleration and deceleration of the following vehicle.

Panwai and Dia [41] (2007) developed another type of neural network for car-following models using a data set from previous research presented by Manstetten *et al.* [42] (1997, as cited in Aghabayk *et al.* [24], 2015). Using this Panwai and Dia [41] developed the car-following behaviour by using the speed of the vehicles and the distance headways. This model was based on maintaining the desired distance headway. A benefit of using a neural network model for car-following behaviour is that it is an adaptive system which can change its structure during the learning phase. This benefit could also be considered a drawback because the model is not transparent. It does not provide insight into its internal workings. In the training process of a neural network model, there is the issue of under-study and over-study phenomenon. The first problem being that there are insufficient data points which makes the model inaccurate. The problem of over-study can be controlled by reducing the total training time, but under-study is a difficult phenomenon to control.

Summary

Artificial intelligence car-following models are quite different from one another. Fuzzy logic models function very differently from neural network models. Fuzzy logic models function by applying fuzzy rules and fuzzy sets whereas neural network model are an adaptive system which changes their structure during the learning phase. This summary is split into two sections; fuzzy logic and neural network models.

Fuzzy logic models make use of fuzzy values, it does not make use of exact equations and magnitudes. Also, the distances, speeds, and accelerations are all relative values instead of absolute. This brings the negative aspects of these types of models which is that identifying the fuzzy rules is difficult, as well as that these models can not take different vehicle types into account at the moment.

Neural network car-following models use training and testing in order to create their model. They are able to take humans' imprecise perceptions into account in their model. The models themselves also get relatively complicated when compared to traditional car-following models. This heterogeneity of human behaviours is effective for a human behaviour study but carries risk with it as well. The learning process can suffer from over- and under-study as well as a lack of transparency. Often the lack of transparency can be fixed by using a black box model to be able to see the inner workings of the AI. The inputs and outputs become transparent but the inner workings and processes will not.

2.3.3. Lane Changing Models

Lane changing models are used to model potential lane changes when simulating traffic. Commonly they are used in combination with car-following models to produce the most realistic driving behaviour. There are 4 man types of lane changing models; rule based models, discrete-choice based models, artificial intelligence models, and incentive based models. These are described by Rahman *et al.* [43] (2013) in a review of many possible lane change models. Table 2.4 describes the limitations and advantages of each type of model and names the specific models per type. This section does not focus on the models that can be used for simulations, but rather their general impact on modelling CAVs. Li *et al.* [44] (2020) describes the possibilities of CAVs in traffic regarding lane changes, as well as a possible lane changing model to use to best simulate them. The difficulty in lane change models with CAVs is the possibility of communication between the vehicles and the infrastructure. The reason for this study being conducted was that many crashes can be attributed to lane changes. According to the paper, in the US there were 240,000 to 610,000 crashes annually due to lane changes. Exploring the impact that lane changes can have on the safety of a road is an integral element for this research. Li *et al.* [45] (2020) explains that lane changing manoeuvres are performed due to traffic heterogeneity of travelling speeds on different lanes. These lane changes can cause disturbances on the traffic flow and driving behaviour, which in turn, has a negative effect on the safety. Although AVs and CAVs are more capable of reacting appropriately to these lane changes, the disturbance is still noticed. Regardless of the lane-changing model used, Li *et al.* [44] (2020) assumes that CAVs would be beneficial for the safety of the road concerning lane changes. The communicative part of CAVs here would have great impact due to the other connected vehicles being able to react to certain lane changes that are occurring upstream.

Table 2.4: Lane-change models

Lane-change models	Type of model	Limitations	Advantages
Gipps Model CORSIM Model ARTEMiS Model Cellular Automata Model Game Theory Model	Rule Based Model	Difficulties in calibrating the model parameters. Uses only primary variables. Binary answers (yes/no)	Simplicity in modelling. Decision process in one simple stage. Small number of variables.
Ahmed's Model Toledo et al. Model	Discrete-Choice Based Model	It is required to calculate probability functions to determine the utility of each choice.	Decide on the basis of maximum gained utility. Probabilistic results instead of binary answers (yes/no).
Fuzzy-Logic-Based Models ANN Model	Artificial Intelligence Models	Difficulties and complexity in fuzzy rules, membership functions. Requires large amount of data.	Consider humans' imprecise perception, requires numerical data, calibrated using optimization algorithm.
MOBIL LMRS	Incentive Based Models	Fit in congestion is unclear. MOBIL only considers operational process.	Small number of parameters. Takes driver variability into account.

Concluding this chapter is a collection of the main findings of the literature review. At first glance, herd immunity for humans and for road traffic have many similarities. The secondary effects (that the resistance to viral risk and crash risk is improved for the entire group except for only the individual) function in a similar fashion that the majority benefits from the inclusion of immunised members/CAVs in the population. The two concepts can almost be directly translated to one another in how they function. Part of this function are the types of variables that affect each concept. Both concepts consider distance, frequency of contact, and traffic/agent volume. Those variables are similar for either concept. Not all variables can be translated so directly, other variables for viral infections includes the viral load that someone is carrying which could loosely translate to the inherent crash risk of a human driver. Not all aspects can be directly translated, but they are similar enough to be able to draw some parallels between the two herd immunity concepts.

In theory, as explained above, it is more than possible that the two concepts can be translated to one another. To check the above statement, a simulation model is created to determine whether this corroborates the theory. Creating such a simulation model requires a safety metric. Part of the research for the safety metric is determining how the use of CAVs affects the choice of a safety metric. Many of the traditional safety metrics like TTC (time-to-collision) and PET (post-encroachment-time) are very direct and do not include anything about the behaviour of the vehicles. In short, time-to-collision and post-encroachment-time are not affected by the type vehicles used. Safety fields is a new development in the world of traffic safety and provides a number of benefits not apparent in other safety metrics. The behavioural field allows for the use of driving behaviour to affect the severity of a conflict and the static field gives all static objects on a road an impact on drivers. TTC and PET only look at other road users when used for simulations, whereas with safety fields, it is possible to look at road users, their behaviour, and the impact of road side objects like trees and the guard rail. It provides a much more complete image of the effects of surrounding objects as well as the differences in driving behaviour.

In order to use the above safety metric, the driving behaviour of a CAV and an HDV has to be defined. For the purpose of safety fields, this is described by 'driving risk' a value between zero and one, where the higher values denote more reckless driving. This driving behaviour is split between CAVs and HDVs. CAVs are assumed to have perfect driving, resulting in a driving risk value of 0, effectively removing the behavioural field for their value of the safety fields. According to Wang *et al.* [1] (2015) a conservative driving risk value would be at 0.2, and risky behaviour at 0.6. Therefore, driving risk is given a value of 0.4 to be between the two types of behaviour. Other ways to distinguish between the types of driving behaviour is reaction time. Reaction time includes the time required to recognise and react to the situation occurring in front of them. Between CAVs and HDVs, CAVs are assumed to be able to instantly react to the actions happening ahead of them, giving them a reaction time of 0. Where HDVs are concerned, they are given a reaction time of 1 second which is considered an optimal reaction time for humans.

For the car-following model, it is necessary to include the driving behaviour differences between humans and automated vehicles. The simulation model is based mainly on the car-following model which is why each car-following model is explored more thoroughly than other parts of the simulation model. As explained, the car-following model has to account for the differences between CAVs and humans. Possibly the most effective (but also time consuming) car-following models are those based on artificial intelligence. These contain a lot of drawbacks though, the processes that those models take are not always transparent and the modes can be under- or over-trained. Although these models could be most effective at modelling heterogeneous traffic, they are beyond the scope of this research. Ultimately the IDM+ (Intelligent Driver Model +) was chosen as the car-following model. This model accommodates transparency, is comprehensible at all stages, and allows for the necessary driving behaviour differences. For IDM+ vehicle headways are used to determine the acceleration of the following vehicle. For this, Martin-Gasulla *et al.* [21] (2019) has used three different headways depending on the following situation, which in turn provides another distinguishing factor between the vehicles. Implementing the reaction times would be the second distinguishing factor between CAVs and HDVs. The chosen model needed to accommodate the use of CAVs. This affected the decision substantially as there are a limited number of aspects in road traffic that are different between CAVs and HDVs. IDM+ offered a straightforward method that was able to include the differences between CAVs and HDVs.

Finally lane-change models were researched to discover the impact that they could have on simulating CAVs. Li *et al.* [44] (2020) explains that lane changes can cause 240,000 to 610,000 crashes annually in the US. CAVs can impact this heavily by reacting more appropriately and effectively absorbing the sudden manoeuvres made by downstream vehicles. The lane-change models were researched to discover the impact that CAVs could have on these models. Especially rule-based models could be changed depending on the type of vehicle regarding the amount of space between vehicles. Due to lower reaction times, CAVs would be better able to fit themselves into tighter spots in traffic. On top of that, due to the possible communication, CAVs can react to manoeuvres occurring downstream and can take necessary precautions to reduce the number of conflicts happening in their environment.

3

Research Methodology

This chapter describes the research methodology for the simulations. This includes the decisions made for which car-following model is used, the lane-changing model that is used, and the metrics of safety that are applied. Additionally, model calibration is described and a sensitivity analysis is discussed. Model calibration is performed by using the literature from the previous chapter to determine the exact values necessary for a freeway scenario. The sensitivity analysis is necessary to determine the effects of both the calibrated parameters as well as other factors like reaction time, desired speed, and desired headway.

3.1. Research Approach

The research approach is described in part in Chapter 1 where the method for the literature review is discussed. The research approach for the simulations is based on the research question presented in Section 1.3. The simulation results should aid the literature review in answering how traffic safety is impacted by Connected Automated Vehicles considering herd immunity. The research approach for the simulations is based on reflecting reality in the most effective manner. The simulations represent a highway on which certain disturbances occur in the form of a lower speed area and an on-ramp. Both of these disturbances cause turbulence because the drivers have to make adjustments to their speeds which in turn affects the headway. The type of data collected is the number of conflicts that occur due to the inclusion of a disturbance. Depending on the type of scenario, the type of disturbance also changes. The number of conflicts that occur relate directly to the turbulence of the road. Each conflict will cause a change in the headway and the speed of the vehicles. To obtain this data, a safety metric must be used. Safety fields are an appropriate safety metric because even though the individual numbers do not mean anything when extracted from the data, it is possible to determine a critical threshold which determines whether a conflict occurs. Determining this critical threshold is part of Subsection 3.2.3 later in the chapter. The critical threshold for conflicts depends on the relative safety field strength that is described in Subsection 2.2.2. Collecting the conflict data and comparing that data between different CAV penetration rates will be the main method of data analysis. These are described in Section 3.3 and Section 3.4 respectively.

3.2. Modelling Approach

To satisfy the research approach, a realistic model is created through the following steps. To remain feasible, the car-following model used is IDM+ (Intelligent Driver Model +). This model is most appropriate for the research purposes because it is transparent, effective for longitudinal car-following scenarios, and easy to understand. What makes the model transparent is that at every point of the simulation it is possible to determine exactly what the model is supposed to do. Each time step can be inserted into the equation with the accompanying speeds and headways to determine what each following vehicle should do. Furthermore, it is more than appropriate for longitudinal car-following scenarios because it uses the preceding vehicle's speed and distance to determine the acceleration of the following vehicle. A car-following model was provided in which the rest of the model was built. Figure 3.1 shows the steps taken to create the model.

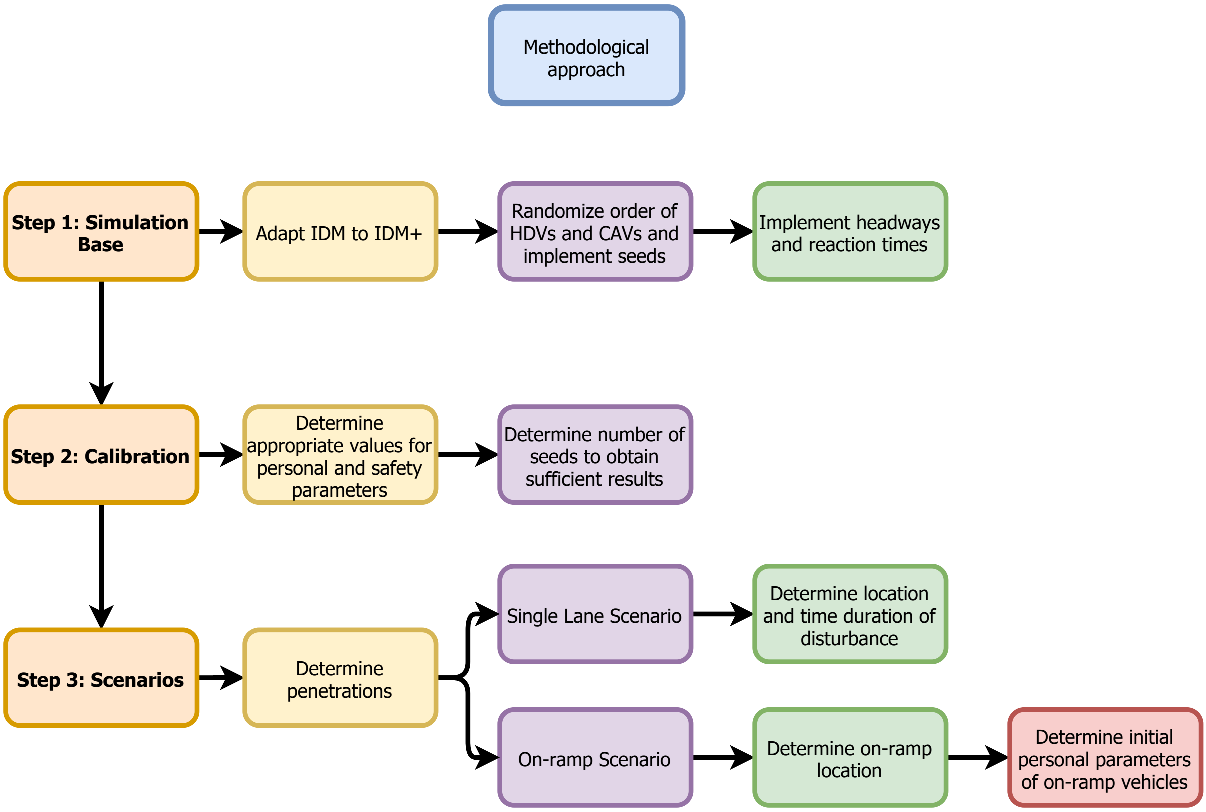

Figure 3.1: Modelling Approach

The above figure can be split into 3 steps. The simulation base, calibration, and scenarios. They are put into this order because each following step can be dependent on its predecessor.

Starting with the simulation base, the simulation model is created. This model is dependent on the research done in Chapter 2. In Chapter 2 decisions are made that affect the input variables of the simulation model. Additionally, the choice of safety metric and car-following model is decided on. As shown in the figure, IDM+ has been chosen for the car-following model. Creating the simulation base is one of the most time consuming processes simply due to it requiring the most programming. This section is also exploratory in sense that it attempts to combine aspects of the safety metric along with IDM+. This step is also responsible for creating the different types of seeded runs. The seeded runs are created by varying the vehicle orders so many combinations of CAVs and HDVs are possible. Then, depending on the following situation headways are implemented. The purpose of each of these steps is to prepare the simulation model for the following steps. The purpose of this research is to discover the safety impacts that CAVs can have and therefore, it is important that the base simulation model properly implements the driving behaviour differences between the two types of vehicles. The results from the model will be based on this difference.

The following step concerns the simulation model calibration. This step is necessary to determine whether the input variables are valid. The calibration step will focus on the driving behaviour to observe what occurs when these values are changed as well as a basic simulation parameter; the number of time steps. On top of that, the results found need to be statistically significant. To ensure that, a test is performed to determine how many seeds are necessary for 95% reliability.

Finally the scenarios will determine what situations will be used. This is split over varying the penetrations as well as varying the type of disturbance that occurs. The disturbances need to make a sufficient impact so that all vehicles will have to react. On top of that, the locations have to be determined. These locations will be based on how long it takes the scenario to reach stability. After that the disturbance can be introduced.

3.2.1. Driving Behaviour

For this section, the specific parameters will be given values. The calibration parameters will be discussed in the next section. Table 3.1 presents the the driving behaviour parameters used for IDM+ with their accompanying values for the simulations. The table shows HDV and CAV parameters to compare the two. Certain parameters do not have any differences between CAVs and HDVs. These are things like comfortable braking speeds and desired speed as these should not differ between types of vehicles. The largest difference exists in the headway and reaction time. The paper by Martin-Gasulla *et al.* [21] investigates the effects of this headway on the throughput of a road. In this research they vary the headway depending on what a CAV is following, ranging from 0.6 seconds to 1.5 seconds. The reaction time exhibited by human drivers is considered the optimal value. The reason this is used is described in the calibration section of the paper.

Table 3.1: IDM driving behaviour parameters

Parameter	Denoted by	CAV value	HDV Value
Comfortable Acceleration	a	0.73 m/s^2	0.73 m/s^2
Desired Speed	v_0	30 m/s	30 m/s
Minimum Headway	s_0	2 m	2 m
Desired time headway	T	0.6/1.5 seconds	1 second
Reaction Time	t	0 seconds	1 second
Comfortable Deceleration	b	1.67 m/s^2	1.67 m/s^2

3.2.2. Simulation Base

To create the simulation base, a model was provided. This model included the IDM as well as the necessary time-stepping and potential disturbances in the MATLAB environment. It was necessary to prepare this model in order to incorporate the necessary additions. These additions include IDM+, different driving behaviours depending on the type of vehicle, and the safety metric. For IDM+ there are two main differences; the headway and reaction times. To apply the differences in headways each vehicle needs to identify the vehicle that they are following. For a single lane scenario this never changes, but as more vehicles are added to the scenario these headways will change. The desired time headway of an HDV following any type of vehicle is 1 second, a CAV following another CAV is 0.6 seconds, and a CAV following an HDV has a headway of 1.5 seconds. These differences are due to the unpredictable nature of HDVs as well as the reaction time. The reaction time is the next part to be implemented into the model. This is done by having the HDVs react to the time step that occurred 1 second previously rather than reacting immediately.

3.2.3. Calibration

This section is necessary to identify the parameters that will need to be calibrated. IDM+ is straightforward to calibrate and has been used many times in the past. Automated vehicles have also been simulated using IDM+. Additionally, it is possible to incorporate a reaction time into the model. This is done by having the following HDVs react to the time step a second before the current time step. This is helpful because it provides flexibility and allows for the differences in driving behaviour for the CAVs and HDVs. For IDM+ the necessary parameters are: the comfortable acceleration, desired speed, minimum headway, desired time headway, the reaction time, and the comfortable deceleration.

Calibration is done for simulation parameters and for safety parameters. The purpose of calibration is to search for a combination of parameter values that will best serve the purpose of the research. In this particular case it means using parameter values that results in the most realistic simulation model, while still remaining feasible in the allotted time-frame. This combination between realism and feasibility is the optimal parameter setup and the main purpose of performing calibration for the simulation model. The personal parameters are initially implemented to be as realistic as possible. Through initial testing of the model these personal parameters are adjusted. This is necessary because the most realistic parameters result in a model that does not reach a steady state for the traffic quickly enough to remain feasible for the simulations (steady state traffic meaning that there is constant velocity for each individual vehicle). To maintain the degree of realism, traffic speeds of Dutch freeways are used. 30 m/s is close enough to these speed limits to use it as the desired speed. The safety parameters are more difficult to calibrate due to the limited research done on safety fields. In the paper by Wang *et al.* [1] the methods for calibrating the safety fields are explained, but each of these make use of the surroundings extensively.

Number of seeds

With simulations it is generally necessary to determine the required number of seeds for statistic significance. The seeds randomise the order of the vehicles. This results in new combinations that can yield interesting results. To determine the number of necessary seeds Equation 3.1 is used.

$$N' \geq t^2_{\frac{1}{2}\alpha,N-1}\left(1+\frac{1}{2}\xi^2\right)\frac{X_s^2}{X_d^2} \tag{3.1}$$

Where:

- N: The sample size.
- X_s: The sample standard deviation.
- X_d: The accepted deviation.
- α: The reliability.
- ξ: The abscissa or normal distribution excess value.
- $t_{\frac{1}{2}\alpha,N-1}$: The value of the student t-test distribution.

This equation makes use of the abscissa but because the results are an average value, the abscissa is equal to zero. The data used for determining the seeds is the number of conflicts that occur. To obtain the necessary data, a conflict needs to be defined. At what values of the safety field strength would a conflict occur. Using Equation 3.2 the relative safety field strength is found per vehicle. An important factor here is defining at what value of the relative field strength a conflict occurs. The severity of conflicts can also be determined, but for calibration purposes, the conflict threshold was set at a safety field strength of 1.9. Using 10 seeds at a penetration of 50% resulted in 28 seeds being necessary per penetration in order to reach 95% reliability. Due to the many seeds and the calculation time necessary per seed, only varying the penetration rates should provide sufficient information for the purpose of this research.

Headways

Initially the headways were set at their optimal values. For a CAV following another CAV this is 0.6 seconds, 1 second for an HDV following any type of vehicle, and 1.5 seconds for a CAV following an HDV. These initial headways caused a good mix of conflicts to occur. In this set up the CAVs with 0 reaction time and a time headway of 1.5 seconds caused 0 conflicts above a relative safety field strength of 1.9 at all penetrations. When adjusting these headways the number of conflicts that occurred drastically changed. Over multiple seeds the standard deviation of the number of conflicts increased by a lot. In order to maintain 95% reliability it would require an incredible increase in the number of runs necessary using Equation 3.1. This would raise it towards levels of 300 seeds in order to keep 95% reliability. 300 seeds is not a feasible number of seeds in the time available. The headway of a CAV following another CAV was changed to 0.8 seconds to provide more space for manoeuvring. With this change, CAVs that follow other CAVs are less sensitive to sudden braking and have some space before it is considered a conflict.

Time step size

The model started with time steps of 1 second, but that also meant that each vehicle only reacted once every second, when driving is a process in which drivers do react more often than that. Realistically, a human driver would react to all stimuli constantly, reducing the time steps further, but that would be difficult to simulate. The time step size of 1 second caused the vehicles to experience a large amount of turbulence without any added disturbance. This was abetted by reducing the time step size to 0.1 seconds so all drivers would react more often which also reduced the overall turbulence on the road.

Reaction Time

Another part of the calibration is the reaction time of the HDVs. Optimal human reaction times are about 1 second. When calibrating the reaction time to go to non-optimal reaction times, the total simulation time is increased. This is because higher reaction times caused additional instability and therefore more time for the model to reach stability. To counteract the instability, the initial distance between vehicles needs to be increased which also affected the total simulation time.

3.2.4. Scenarios

This section describes the different scenarios used for data collection. These scenarios have the purpose of simulating turbulence and that turbulence should cause safety conflicts. Then, by using different penetration rates the number of conflicts can start to change which makes it possible to compare those different penetration rates. Furthermore, each scenario can also be varied in other ways like total traffic volume, or through the personal parameters. Table 3.2 shows the scenarios as well as the variables per scenario. Each of the scenarios could increase in traffic volume, in these cases it might be necessary to adjust to total simulation time as well as change the location of the disturbance. This would happen because the model would take longer to reach stability.

Baseline

A baseline scenario is created to see whether any conflicts occur with the current relative threshold for the safety fields. This is simply the same scenario as the scenario with the disturbance, but then lacking the disturbance. Headways and reaction times will still be changed depending on the identity of each vehicle. If many conflicts occur during the baseline scenario then either the threshold for conflicts will have to be adjusted or some personal parameters so that those conflicts do not occur.

Scenario 1: Single lane highway with a disturbance

This scenario is used to show how the vehicles react to a disturbance occurring on a single lane highway. This is the starting scenario as it is also the most simple. The purpose of this disturbance is to cause turbulence. The turbulence in turn causes safety conflicts due to the many changes in speed and headway that the network of vehicles experiences.

The disturbance on this single lane highway causes a decrease in the speed of all vehicles passing a certain point. This is ideal to cause turbulence on the road and forces conflicts to occur. The disturbance is created by designating a time period to have a lower speed. The lower speed only applies to the first vehicle in the queue and this will cause all following vehicles to react to this speed difference. The disturbance will occur at a distance of 5500 meters from the start, and continues for 500 meters till 6000 meters. This location is chosen so that the traffic has enough time to stabilize before a disturbance occurring. At higher vehicle volumes this could be put on a later time step because the disturbance could cause a stop-and-go wave that spills back to the start of simulation. Additionally, with higher traffic volumes the total number of time steps could increase from 5000 time steps (0.1 seconds per time step) to a high value in order to fit all the vehicles in the allotted space.

Table 3.2: Scenarios

Scenarios	Seeds	Driving dynamics	Penetration rate
Baseline	1	IDM+	0, 10, 20, 30, 35, 40, 45, 50, 55, 60, 65, 70, 80, 90, 100
Single lane disturbance	28	IDM+	0, 10, 20, 30, 35, 40, 45, 50, 55, 60, 65, 70, 80, 90, 100

3.3. Data Collection

Data collection will occur through through the simulations. All data that is used for those simulations can also be collected. Everything is saved in the MATLAB environment which makes it possible to call every piece of data that has been used throughout the simulation. This is why transparency has been mentioned so often as a benefit of using the intelligent driver model. The type of data collected is quantitative due to it being a simulation. This will also be the only type of data collected throughout the simulation because the topic of research is very niche and no past research fits the research question in a similar manner. The main results will be based on the safety fields. This includes both the dynamic field as well as the behavioural field. Safety fields is described in Chapter 2. The magnitude of the safety fields describes the severity of the conflict between the two vehicles. Safety fields are used as the safety metric because it applies both a behavioural field as well as a kinetic field. The data collected is the number of conflicts, and each of these conflicts falls into a certain level of severity based on their relative safety field strength. The relative safety field strength is described by Equation 3.2. The formula for the relative safety field strength is also described there. The ranges for these severities are 0-1, 1-1.5, 1.5-1.8, 1.8-2.1, and >2.1. This severities simply

3.4. Results Analysis

The simulation results only gain meaning when a disturbance is added to the scenario, in order to determine the effectiveness of each penetration of CAVs. Until the simulation has reached stability, the conflicts recorded can be ignored. Data collection should start from the moment the disturbance has effect. A critical step for the data analysis is ensuring that outliers are ignored because they can impact the total number of conflicts that occur during a run. Outliers are defined as vehicles that make extreme manoeuvres during the simulations. The results are analysed by finding the strength of the relative safety field per different car-following situation as described by Equation 3.2. Additionally, single runs will be performed to visualise the effect that the disturbance has on the rest of the vehicles. Furthermore, the total conflicts per penetration rate at each severity level can be compared and analysed.

The total number of conflicts per penetration rate can be tested using the independent samples t-test for significance. Although 28 simulation runs are done per scenario, testing for significant difference can still be effective. This test provides certainty that the differences in the values between the different penetration rates is significant. Furthermore, descriptive statistics will be used to point out any obvious trends in the data.

Relative safety field

In the simulation environment the only objects affecting the safety field strength are the other vehicles and the driving behaviour of the vehicle. The proposed values in that research paper will be used because the trial simulations showed results that can be compared with one another. No extreme values were found which makes it possible to establish a scale of severity for the safety field values. This threshold not be the absolute value of what the safety fields provide, but rather a relative value. This is because safety fields are affected by distance between vehicles, and due to the headway depending on what vehicles are following one another, a relative value would make more sense to compare. A CAV following another CAV has a lower headway which would point towards there being a higher safety field strength which would indicate a higher chance of there being a conflict, when this should not be the case. This the relative safety field strength value was calculated as shown by Equation 3.2. This is necessary in order to compensate for the limitation of safety fields that vehicles with different headways will have different safety field strengths that they tend towards during stable road conditions.

$$E_{R,\ i,\ t} = E_{i,\ t} - E_{i,\ F} \tag{3.2}$$

Where:

- $E_{R,\ i,\ t}$: Relative field strength of vehicle i and timestep t.
- $E_{i,\ t}$: Field strength of vehicle i at timestep t.
- $E_{i,\ F}$: Field strength of vehicle i at final timestep.

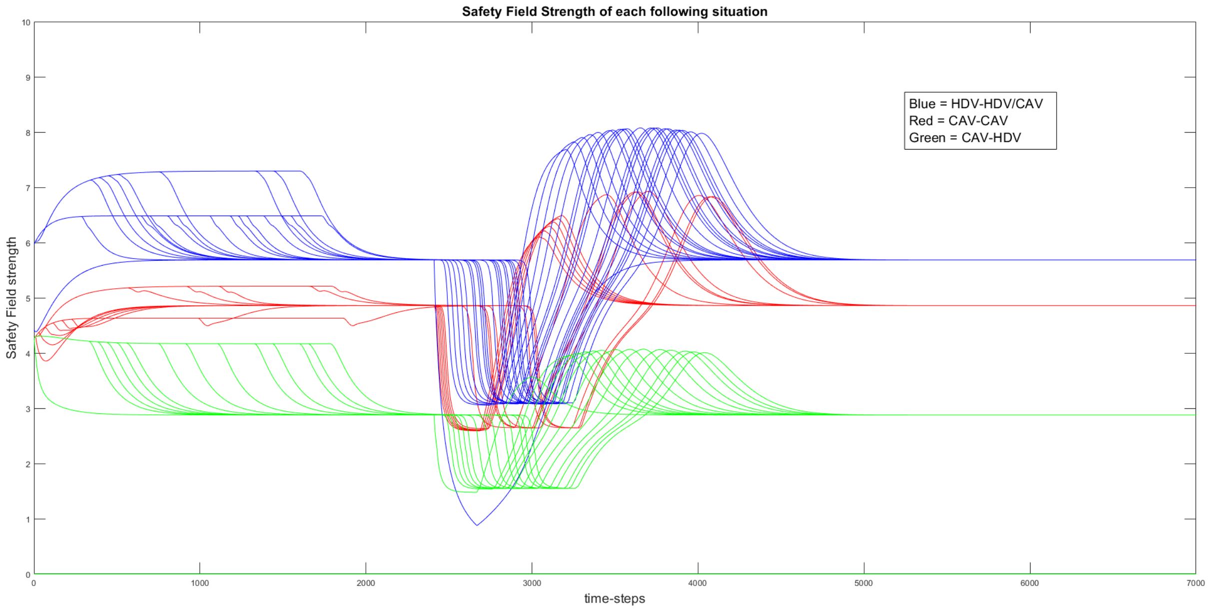

Figure 3.2: Safety field Strength in each following situation

Figure 3.2 shows a single run where each single line represents a vehicle. Its colour represents the type of following situation as shown in the legend. The figure illustrates how each type of following situation returns to a separate baseline. This is what the relative safety field strength will counteract. Figure 3.3 shows the relative safety field strength of a single run. This way the conflicts can be compared more effectively with one another. These figures are used to illustrate the effects of Equation 3.2. The second figure clearly shows that the safety field strengths are closer to one another to compensate for the differences created by the different headways of the following situations.

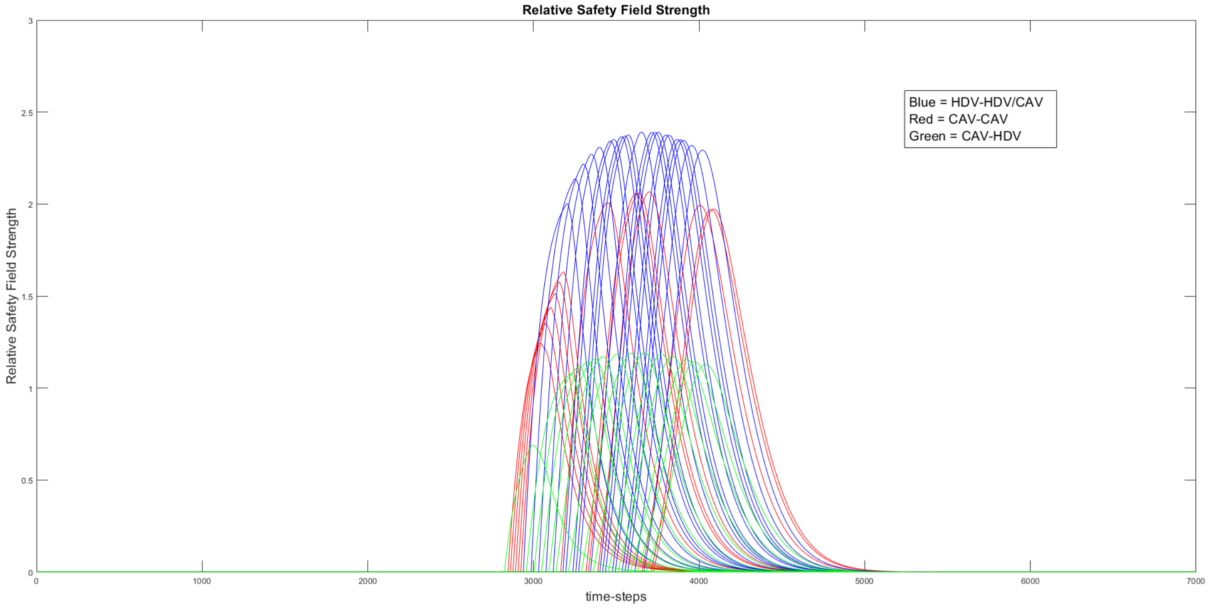

Figure 3.3: Relative Safety Field Strength of a single run

The relative safety field strength can be found by subtracting the safety field strength value that each individual vehicle tends towards. When the disturbance is resolved and the model reaches stability; 0 changes in speed and acceleration, each individual vehicle will have a certain safety field strength. This safety field strength is denoted by $E_{i,\,F}$. This is the value of the safety field that each individual vehicle tends towards. To give meaning to the relative safety field values, a scale for the severity of conflicts is created. This scale is based on the collected results of the model. With a maximum relative safety field value of 2.53, the upper limit of the scale is at 2.6 and the lowest is 0. This upper limit is limited to this scenario.

4

RESULTS

This chapter discusses the direct simulation results, a sensitivity analysis for robustness, and analyses the results using statistical testing.

4.1. SIMULATIONS

The results of the simulations are based on the scenarios that are tested. The scenario was tested using 28 seeds at each penetration to vary the vehicle order. In order to interpret the data, the definition of a conflict for this simulation situation should be clarified. Measuring the level of safety is done using the safety metric safety fields. This safety metric makes use of the leading and following vehicle's velocity and distance from one another to determine the safety field strength. This is then adjusted to find the relative safety field strength at every time step. A conflict in this situation can be defined as having a relative safety field strength greater than 0, but that would result in a conflict every time a micro-adjustment is made to the speed of a vehicle as the following vehicle will react. Therefore the term conflict severity is used. This term describes how dangerous the conflicts are through the use of value ranges of the relative safety field strength. The higher the values of the relative safety field strength, the more dangerous the conflicts. A combination of the number of conflicts and the conflict severity reflects the safety of the scenario. Therefore, the crash risk would increase when the conflicts get more severe and numerous, and subsequently the level of safety would decrease.

To introduce the results Figure 4.1 shows a single run of the model at 50% penetration. Figure 4.1 is similar to Figure 3.2 and Figure 3.3 because it shows the relative safety field strength at each timestep as well as the vehicle number in the queue.

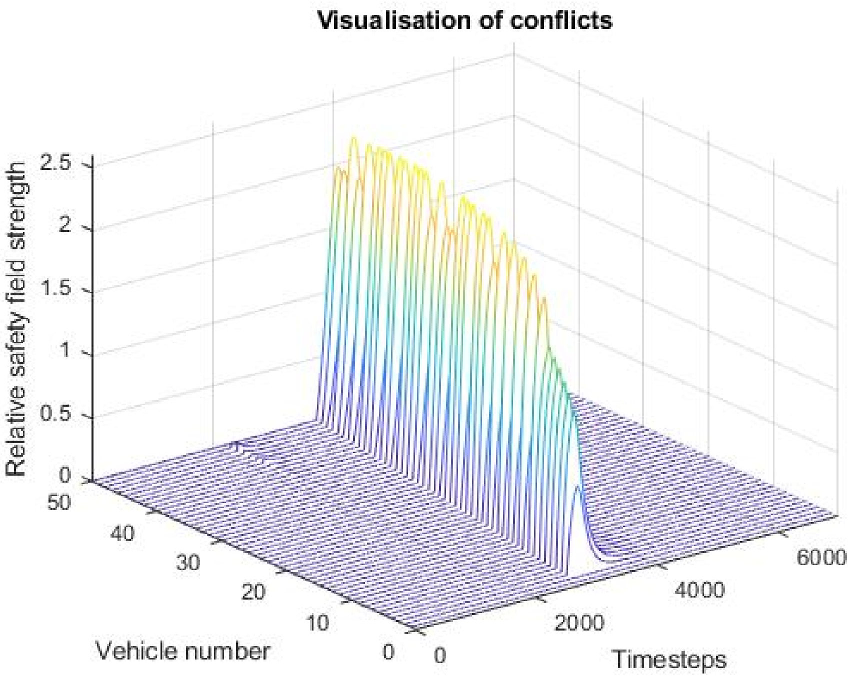

Figure 4.1: Visualisation of conflicts at 50% penetration

The above figure shows the number of conflicts to happen per vehicle at each timestep. As expected, the number of conflicts is low for the first few vehicles and that number grows as the simulation time increases. The relative safety field strength is shown to vary between just under 2 and between 2 and 2.5. These values change due to the different following situations that occur. This figure in itself is not enough to draw any conclusions, and as such, other tables and figures are included below.

Table 4.1 shows the number of conflicts per severity range at each penetration rate. This table is used to show the total number of conflicts that occur at each penetration. Conflict severity is what makes it possible to compare the CAVs with the HDVs. The conflict severity is based on the relative safety field strength and it provides the possibility to compare the number of conflicts over each separate threshold.

Table 4.1: Number of conflicts per conflict severity and penetration

Conflict Severity	**0**	**10**	**20**	**30**	**35**	**40**	**45**	**50**	**55**	**60**	**65**	**70**	**80**	**90**	**100**
1-1.5	5682	6147	6392	6636	6748	6841	6928	6949	6940	6879	6915	6818	6852	6429	6189
1.5-1.8	3159	3169	2953	2795	2766	2702	2736	2783	2847	2902	2994	3142	3556	3860	4481
1.8-2.1	3250	3159	3159	3135	3197	3169	3201	3340	3441	3663	3861	4192	4853	5439	6192
>2.1	8433	7260	6206	5406	5076	4769	4327	3862	3521	3172	2762	2466	1699	1201	661
Total	20524	19735	18709	17972	17787	17482	17192	16934	16749	16616	16531	16618	16960	16929	17523

Table 4.1 ignores the range of a relative safety field strength value of 1 or below, because these are not considered conflicts. These values are too mild to consider them as conflicts. The table ignores the vehicle orders for now, simply to show how the number of conflicts changes over the penetrations. At a relative safety field strength of above 1, the least number of conflicts are found at 65%. The highest number of conflicts is found at a penetration rate of 0%. As assumed, the total number of conflicts seems to decrease as the penetration of CAVs increases, but it was not expected that the lowest number of conflicts would occur at 65%. This does account for all conflicts so it does not yet consider the severity of these conflicts. At a relative safety field strength of more than 2.1, the number of conflicts decreases almost linearly over the penetration rates. The decrease per penetration rate does start at a higher rate and the change decreases as the penetration rate increases.

Table 4.2: Change in number of conflicts per penetration

Penetration (%)	0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100
Change	1173	1054	799	637	907	690	706	767	498	540

Table 4.2 shows the change in the number of conflicts per penetration rate at a severity threshold of 2.1. As shown the relationship is not linear, but the number of conflicts does decrease a substantial amount. At 100% penetration, the total number of conflicts is about 3000 conflicts fewer than at 0%. This does not tell the whole story, as there are far more severe conflicts at 0% than at 100% penetration.

Per severity range the types of conflicts were also collected. The types of conflicts are defined by the types of following situations. There are four possible following situations; HDV following an HDV, HDV following a CAV, CAV following a CAV, and CAV following an HDV. The types of conflicts that occur provide insight into which situations are most dangerous. Table 4.3 shows the number of conflicts for each following situation at a relative safety field strength of more than 2.1.

Table 4.3: Relative safety field strength >2.1 conflict types per penetration

Threshold >2.1	**0**	**10**	**20**	**30**	**35**	**40**	**45**	**50**	**55**	**60**	**65**	**70**	**80**	**90**	**100**
HDV-HDV	8433	6535	4986	3745	3321	2790	2281	1827	1457	1174	875	703	239	52	0
HDV-CAV	0	700	1163	1578	1646	1825	1872	1846	1821	1722	1644	1452	1076	620	0
CAV-CAV	0	25	57	84	110	154	175	190	244	276	242	312	384	529	661
CAV-HDV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

The above table indicates that HDVs are part of most conflicts to occur for the severity level of more than 2.1. Even at 90% penetration where the majority of vehicles are CAVs, there are more conflicts with HDVs following CAVs than CAVs following CAVs. Figure 4.2 shows the graph from which it is possible to view the trend.

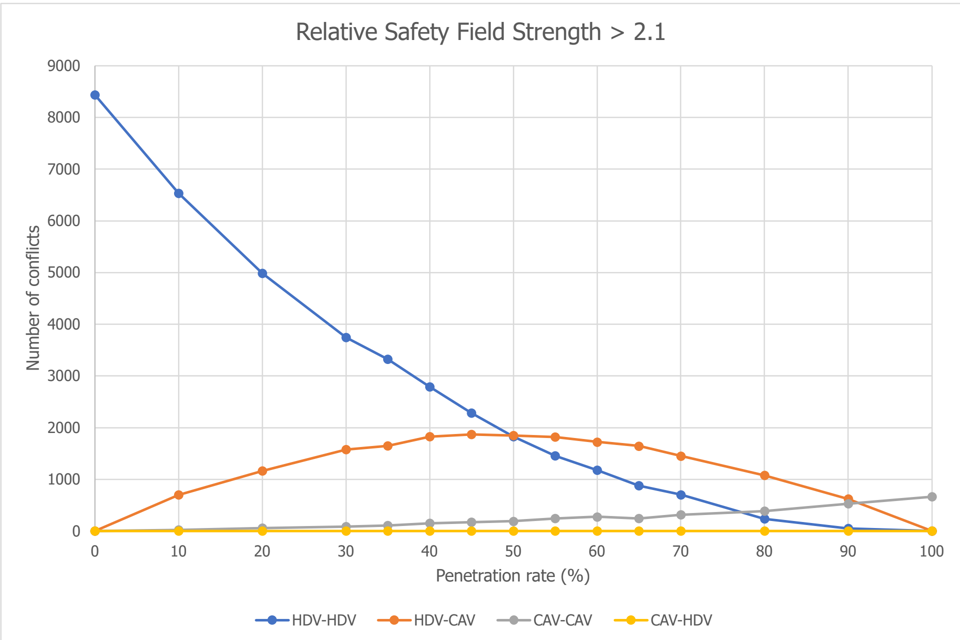

Figure 4.2: Relative safety field strength threshold above 2.1

As depicted by the figure above, there are no crashes in the following situation of CAV behind an HDV. This is a trend that holds true for most thresholds. Only at the relative safety field strength threshold of 1 to 1.5 are there any conflicts in that specific following situation. Altogether, the total number of conflicts decreases as the penetration rate increases. It is necessary to compare this to the other threshold levels to determine whether this trend continues. Table 4.4 shows the relative safety field strength value from 1.8 to 2.1 for each penetration rate and following situation.

Table 4.4: Relative safety field strength 1.8 to 2.1 conflict types per penetration

Threshold 1.8-2.1	0	10	20	30	35	40	45	50	55	60	65	70	80	90	100
HDV-HDV	3250	2776	2330	1845	1609	1382	1128	931	732	596	451	353	156	30	0
HDV-CAV	0	330	602	835	896	965	1014	1023	983	914	878	762	591	313	0
CAV-CAV	0	53	227	455	691	822	1059	1386	1726	2154	2532	3077	4106	5096	6192
CAV-HDV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

What can immediately be observed is the larger number of conflicts for CAVs following CAVs at 100% penetration. This value is also a lot higher than the total number of conflicts at 0% penetration. What this shows is that CAVs are better able to deal with most conflicts, but the more severe conflicts are moved to lower conflict thresholds. Figure A.1 depicts the number of conflicts in the range from 1.8 to 2.1 at each penetration rate and following situation.

Figure A.1 clearly shows that the total number of conflicts for CAVs following CAVs is a lot larger than that of the HDVs following other HDVs. By looking at the total number of conflicts that are above a relative safety field strength of 1.8, it is possible to see which penetrations and following situations have more conflicts. This is depicted by Table 4.5.

Table 4.5: Relative safety field strength greater than 1.8 per penetration

Threshold >1.8	0	10	20	30	35	40	45	50	55	60	65	70	80	90	100
HDV-HDV	11683	9311	7316	5590	4930	4172	3410	2758	2189	1770	1326	1056	395	82	0
HDV-CAV	0	1031	1764	2413	2542	2791	2886	2868	2803	2636	2522	2213	1667	933	0
CAV-CAV	0	77	285	539	801	976	1233	1576	1970	2429	2775	3389	4490	5625	6853
CAV-HDV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	11683	10419	9365	8542	8273	7938	7528	7202	6962	6835	6623	6658	6552	6640	6853

This table shows that the total number of conflicts that occur is lower at 100% penetration than at 0%. The least number of conflicts occurs at 80% penetration. The results from the above table show that CAVs were better able to deal with situations deemed more extreme. As the penetration rate increases both the number of conflicts decreases, as well as the severity of those conflicts. To illustrate this, Figure 4.3 shows the figure where the relative safety field strength is above 1.8.

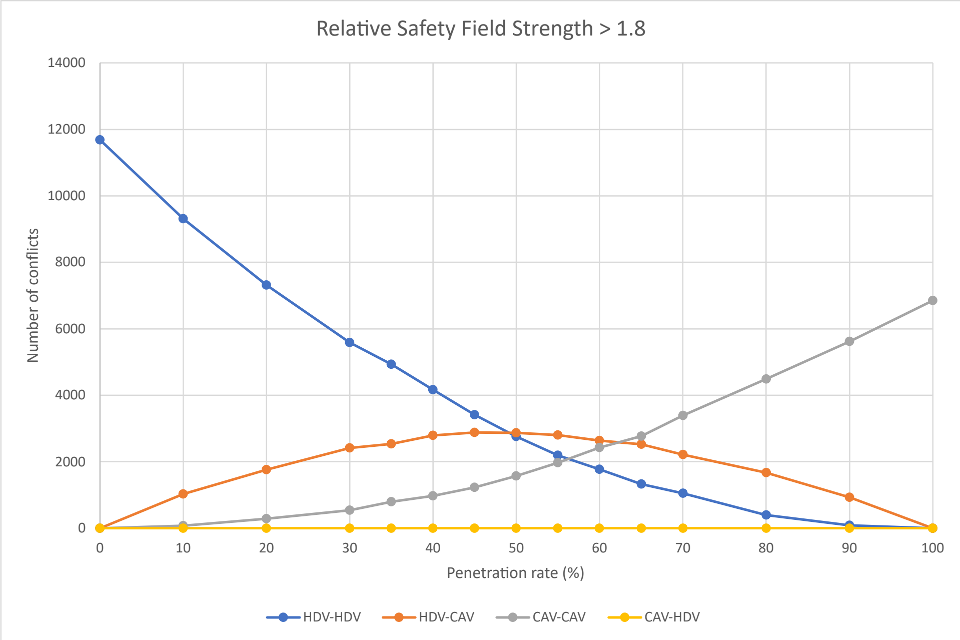

Figure 4.3: Relative safety field strength threshold greater than 1.8

The purpose of the above figure is to show how each conflict scenario varies over the penetration rate. Clearly the total number of conflicts is a lot lower at the higher penetration rates.

Table 4.6: Relative safety field strength 1.5 to 1.8 conflict types per penetration

Threshold 1.5-1.8	0	10	20	30	35	40	45	50	55	60	65	70	80	90	100
HDV-HDV	3159	2817	2229	1676	1473	1234	1026	851	649	523	398	304	133	30	0
HDV-CAV	0	323	560	746	777	842	878	895	864	793	759	636	565	260	0
CAV-CAV	0	29	164	372	516	626	832	1037	1335	1587	1837	2202	2858	3569	4481
CAV-HDV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 4.7: Relative safety field strength 1.0 to 1.5 conflict types per penetration

Threshold 1-1.5	0	10	20	30	35	40	45	50	55	60	65	70	80	90	100
HDV-HDV	5682	4667	3748	2824	2511	2121	1763	1444	1118	918	702	548	241	45	0
HDV-CAV	0	534	921	1263	1302	1398	1480	1492	1444	1358	1320	1112	906	470	0
CAV-CAV	0	56	244	567	857	1043	1340	1689	2109	2459	2843	3325	4186	4984	6189
CAV-HDV	0	890	1479	1982	2077	2279	2345	2324	2268	2144	2050	1833	1519	931	0

Table 4.6 and Table 4.7 show the tables of the relative safety field strength of the thresholds of 1.5-1.8 and 1-1.5. These tables are quite similar except for the CAV following an HDV situation finally has conflicts. Furthermore, the conflicts transfer from the HDV following an HDV situation to the CAV following a CAV situation. This is what happens across all different conflict thresholds due to the change in the penetration of CAVs.

From the collected results above, it is clear that there are benefits that CAVs provide. Not only does the total number of conflicts decrease, their severity is also reduced. This is clear from the graphs showing the relative safety field strength of above 2.1 and 1.8. In the milder thresholds CAVs take part in more conflicts than HDVs, but this is because they lack so many of the conflicts above the threshold level of 2.1. The tables used show the exact number of conflicts per scenario. When considering all conflicts, it was unexpected that the least number of conflicts would occur at a penetration rate of 65%. This is subject to change depending on on what can be defined as a conflict. Currently everything above a relative safety field strength of 1 is considered a conflict, but if this value would increase, then the conflict numbers at 80% or 90% penetration would be the least over all the penetration rates. As the current results show, CAVs have the fewest critical conflicts and these can be the most important where safety is concerned. There are other inputs that can also have an impact if they are changed. These are described in the following Section 4.2.

4.2. Sensitivity Analysis

A sensitivity analysis is performed to determine the effects that changing a single variable has on the rest of the simulation. During calibration many of the parameters were tested to find the optimal set up for the simulations. Those parameters are not taken into account as their values have already been justified. The sensitivity analysis concerns the 'driving risk' value of humans, maximum acceleration/deceleration, and the desired speed during the disturbance. The 'driving risk' value is the value that is used in the safety fields calculations. The sensitivity analysis tests the robustness of the model and increases the understanding of the relation between the input variables and output variables.

4.2.1. Driving Risk

Driving risk is the variable used in the safety metric of safety fields, given to the human drivers to differentiate their behaviour from that of the CAVs. Inherently it is assumed that CAVs do not make mistakes while driving and thus their driving risk is set to 0. Driving risk range from 0.2 to 0.6 to determine the effect of this parameter and which value is appropriate for this research. The effect of changing this value is determined through the number of conflicts that occur at each level of severity.

As expected, when the driving risk value of humans increases, so do the number of conflicts that occur at each severity. This is due to the safety field strength increasing even compared to its new relative safety field strength. Table 4.8 shows the gradation of the conflicts per penetration. As shown, the driving risk clearly increases the number of conflicts at each penetration except at a 100%. This is logical because the driving risk directly impacts the HDVs and not the CAVs, which explains why at 100% penetration the conflict values are constant.

Table 4.8: Driving risk safety field strength above 2.1 per penetration

Driving risk	**0**	**10**	**20**	**30**	**35**	**40**	**45**	**50**	**55**	**60**	**65**	**70**	**80**	**90**	**100**
0.2	2058	1662	1346	1156	1130	1046	914	788	741	657	534	577	487	570	661
0.3	6165	5186	4309	3705	3495	3276	2936	2580	2353	2136	1823	1693	1208	946	661
0.4	8433	7260	6206	5406	5076	4769	4327	3862	3521	3172	2762	2466	1699	1201	661
0.5	10051	8766	7599	6655	6250	5878	5347	4805	4351	3913	3426	3031	2084	1370	661
0.6	11316	9980	8766	7735	7250	6815	6208	5590	5029	4505	3939	3456	2364	1505	661

Figure 4.4 expands on the claims made that higher driving risk results in more conflicts. It especially illustrates the change in the slope per penetration rate. At a driving risk of 0.6, the largest number of conflicts occur, but it also has the highest slope of each driving risk value. Since the driving risk has no impact on the number of conflicts for CAVs following other CAVs, each of the lines gathers towards the same number of conflicts.

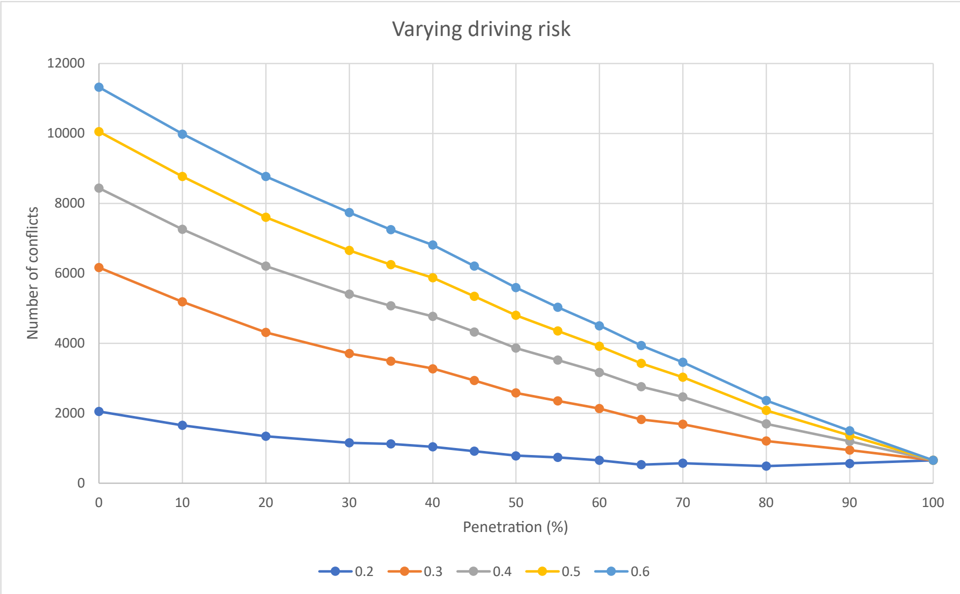

Figure 4.4: Varying driving risk conflicts per penetration rate

4.2.2. Maximum Acceleration

Maximum acceleration affects the change in speed of every vehicle. For car traffic this variable can be split into two versions, a comfortable and a maximum acceleration. Maximum acceleration is based on what the vehicle is capable of. It is assumed that the physical capabilities of the simulated vehicles is homogeneous across all HDVs and CAVs. The maximum acceleration will vary from 0.8 m/s^2 to 1.2 m/s^2 with 1.0 m/s^2 being the original value used for calibration.

For the maximum acceleration it is hypothesised that the higher values will cause more conflicts. This is due to the vehicles needing more time to reduce their acceleration back to zero, so on average they would be closer to the vehicle that they are following. Especially HDVs could suffer from this due to the higher speeds that they reach with a reaction time of 1 second. Table 4.9 shows the number of conflicts above the threshold relative safety field value of 2.1 at each penetration.

Table 4.9: Maximum acceleration safety field strength above 2.1 per penetration

Maximum Acceleration	0	10	20	30	35	40	45	50	55	60	65	70	80	90	100
0.80	5557	5089	4601	4101	3831	3560	3216	2853	2527	2232	1929	1615	972	480	0
0.85	6332	5684	5051	4460	4167	3858	3488	3092	2747	2431	2105	1787	1079	551	0
0.90	7063	6236	5465	4786	4473	4148	3759	3332	2967	2619	2266	1926	1184	622	0
0.95	7835	6825	5912	5172	4851	4536	4107	3648	3293	2938	2540	2187	1422	863	118
1.0	8433	7260	6206	5406	5076	4769	4327	3862	3521	3172	2762	2466	1699	1201	661

Figure 4.5 depicts the graph for the data presented in Table 4.9. The purpose of this depiction is to show how the slope changes per different maximum acceleration. The maximum acceleration has a limited effect on the number of conflicts and they remain similar throughout. Only at the earlier penetrations is the number of conflicts substantially different. They tend towards each other as the penetration rates increase.

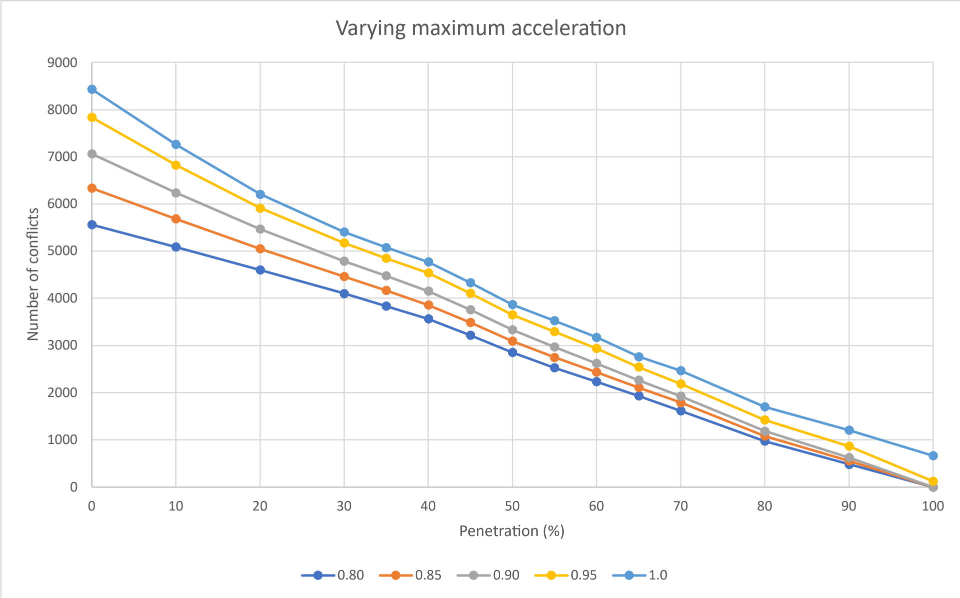

Figure 4.5: Varying maximum acceleration conflicts per penetration rate

4.2.3. Maximum Deceleration

The maximum deceleration is similar to the maximum acceleration because it is split into two categories. Comfortable deceleration and maximum deceleration. Comfortable deceleration is generally around 3 m/s^2 and maximum deceleration at 5 m/s^2. It will vary from comfortable deceleration to maximum deceleration to determine its effects on the number of conflicts and their severity.

The maximum deceleration does not have a clear trend that is followed by all penetration rates. At 100% penetration, the number of conflicts remains very similar at each maximum deceleration. The earlier penetrations do suffer from an increase in the number of conflicts when the maximum deceleration increases. This is what is expected because vehicles must react more quickly and with a higher deceleration, which in turn increases the turbulence of the entire road and therefore increases the number of conflicts. At higher penetrations the number of conflicts becomes more consistent and the magnitude of the changes is limited. The table showing the penetration rates and maximum deceleration is shown by Table 4.10.

Table 4.10: Maximum deceleration safety field strength above 2.1 per penetration

Maximum Deceleration	0	10	20	30	35	40	45	50	55	60	65	70	80	90	100
-3.0	6438	5778	5114	4484	4196	3929	3602	3238	2915	2624	2337	2068	1524	1127	665
-3.5	6661	5932	5221	4570	4279	4006	3670	3295	2974	2679	2383	2108	1544	1148	663
-4.0	7116	6258	5455	4764	4463	4183	3822	3428	3107	2801	2484	2202	1595	1188	669
-4.5	7826	6788	5845	5096	4783	4490	4086	3657	3323	3004	2640	2346	1674	1195	664
-5.0	8433	7260	6206	5406	5076	4769	4327	3862	3521	3172	2762	2466	1699	1201	661

Figure 4.6 shows the data from Table 4.10. Similarly to the maximum acceleration, the total number of conflicts is substantially different at the earlier penetrations. Later penetrations all tend towards the same number of conflicts which is separated by very few conflicts. A lower maximum deceleration results in fewer conflicts occurring, which would mean that the drivers and CAVs react in a milder fashion to vehicles slowing down in front of them which could create a conflict between those two vehicles, but it causes less of a disturbance for the vehicles upstream.

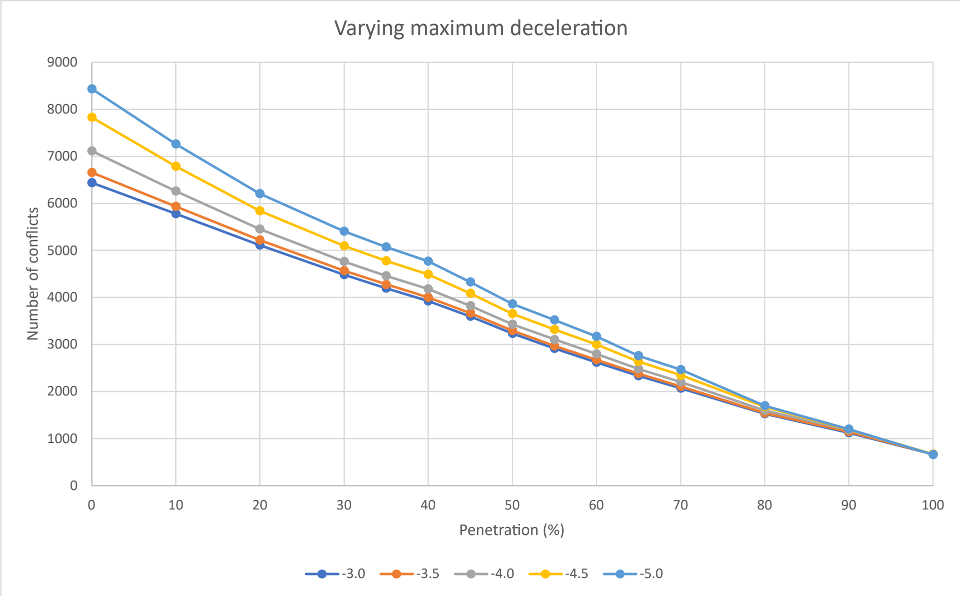

Figure 4.6: Varying maximum deceleration conflicts per penetration rate

4.2.4. Speed during disturbance

The speed during the disturbance denotes the severity of the disturbance. The disturbance causes the vehicles to heavily reduce their speeds which causes a shock wave effect upstream. The disturbance causes the conflicts to occur but the value of the reduced speed can have a large impact on the number of those conflicts. The reduced speed of the disturbance will vary from 12 m/s to 18 m/s with 15 m/s being the original value used during calibration.

The speed during the disturbance has a direct impact on the number of conflicts at a relative safety field strength threshold value of more than 2.1. The lower the disturbance velocity, the more conflicts at every single penetration. As the disturbance velocity increases, the number of conflicts decreases. This is because the difference between the desired velocity and disturbance velocity decreases as the disturbance velocity increases. When this difference becomes smaller then the vehicles have a lower change in velocity which results in fewer conflicts occurring. Table 4.11 shows the total conflicts per penetration rate and disturbance velocity.

Table 4.11: Disturbance velocity safety field strength above 2.1 per penetration

Disturbance Velocity	**0**	**10**	**20**	**30**	**35**	**40**	**45**	**50**	**55**	**60**	**65**	**70**	**80**	**90**	**100**
12	15086	13740	12448	11115	10597	10061	9467	9048	8544	8099	7685	7180	6129	5167	3978
13	12810	11488	10268	9137	8683	8226	7701	7285	6848	6448	6052	5630	4683	3839	2960
14	10656	9406	8254	7291	6894	6511	6028	5588	5198	4843	4450	4104	3243	2495	1844
15	8433	7260	6206	5406	5076	4769	4327	3862	3521	3172	2762	2466	1699	1201	661
16	4187	3551	2901	2468	2309	2137	1906	1649	1473	1316	1162	1057	696	377	0
17	1547	1130	805	642	594	537	449	366	317	254	198	177	80	61	0
18	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0

Figure 4.7 shows how the number of conflicts varies per different disturbance velocity. Varying the disturbance velocity results in the largest differences in the number of conflicts, ranging from 15,000 conflicts to 0 conflicts at a penetration rate of 0. What Figure 4.7 especially shows is that the lowest disturbance velocities have a more extreme slope. This slope becomes milder as the disturbance velocity increases.

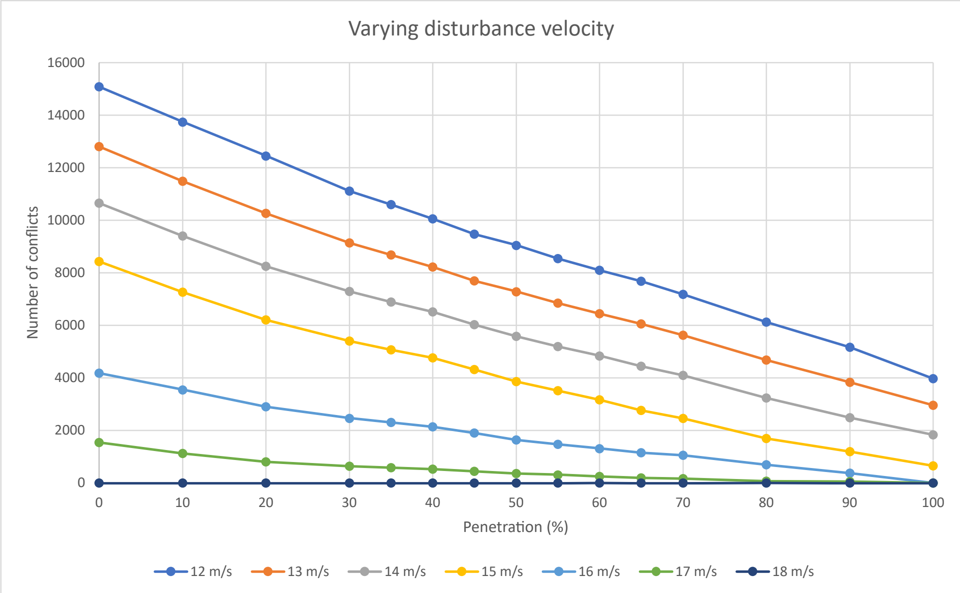

Figure 4.7: Varying disturbance velocity conflicts per penetration rate

4.2.5. Sensitivity Analysis Summary

From each of the inputs tested in the sensitivity analysis, the number of conflicts changed according to the increase in the input variable. This section seeks to answer whether it is necessary to change any of the input variables. For driving risk, a value of 0.4 seems appropriate. It denotes medium driving risk for humans and has been used in previous research to denote standard driving. The other input variables should also remain as they are, changing any of the parameters results in a change in the total number of conflicts, but each value was chosen during the literature review as being the most appropriate value. A maximum deceleration of -5 m/s is quite standard, even if it is less than the comfortable deceleration, it better reflects potential emergency braking. The maximum acceleration should also remain at its current value of 1 m/s because the lower values of the acceleration reduce the number of conflicts quite heavily. At 100% penetration there are barely any conflicts and the maximum value of 1 m/s is based on the literature. The speed during the disturbance affects the number of conflicts most heavily. Any of the velocities above the original 15 m/s results in very few conflicts at the higher penetration rates. Therefore the higher disturbance velocities should not be used. At the lower disturbance velocities, the number of conflicts increases heavily, even at the higher penetration rates. Due to this extreme increase, 15 m/s remains an appropriate value for the reduced velocity during the disturbance.

The sensitivity analysis also gave light to the changes in the slopes of each variable as they were varied. Especially driving risk and disturbance velocity had a large impact on the slope whereas the maximum deceleration and acceleration were more mild. Especially driving risk followed the expectation where it directly impacted the number of conflicts depending on its value. The higher this driving risk variable, the higher the total number of conflicts. The sensitivity analysis shows that changing any of these variables would have a significant impact on the number of occurring conflicts. Even the ones where the change seems minimal, the difference between the maximum and minimum values tested result in a change of at least a thousand conflicts. This is a substantial difference and it shows that the number of conflicts is stable when changing an individual parameter. The part that does remain stable over the different parameter changes would be the trend of the number of conflicts over the penetration rate. Only the disturbance velocity shows a larger change in the trend by having 0 conflicts occur at the higher disturbance velocities.

5

Discussion

This chapter is used to interpret and discuss the results found in Chapter 4, address the limitations inherent to the research, and provide recommendations to continue and improve the research.

5.1. Major findings

This section is aimed at summarising the major findings of the literature review and the simulation model. Both the literature review and the simulation model aimed towards answering the research question 'How is traffic safety influenced by connected (automated) vehicles considering the concept of herd immunity?' From both the literature review and the simulation model, the results indicate that traffic safety is positively influenced by the introduction of connected automated vehicles. They provide benefits beyond the direct safety benefits that AVs provide, because the communicative part allows them to absorb the mistakes of human drivers more effectively. The simulation model does well to show that, as the penetration rate increased not only do the total number of conflicts decrease, also their severity is decreased. The sensitivity analysis demonstrated how the number of conflicts would change as certain simulation inputs were changed. Especially the inputs of 'driving risk' and disturbance velocity had a huge impact on the number of conflicts. 'Driving risk' is the value used to describe driving behaviour for the calculations of safety fields. As the 'driving risk' increased so did the number of conflicts for HDVs, and the disturbance velocity changed the number of conflicts for all drivers involved.

5.2. Interpretation of results

This section is used to discuss the significance of the results and how they answer the research questions.

Literature review

The literature review demonstrates that the concept of herd immunity can be used for both viral infections and for traffic safety. Many of the indicators used for either concept can be translated to one another. These indicators include distance, agent/vehicle volume, and frequency of contact. Not only that, but both concepts consider both the primary and secondary effects of herd immunity. According to John and Samuel [13] (2000) the definition of herd immunity is "The resistance of a group to attack by a disease because of the immunity of a large proportion of the members and consequent lessening of the likelihood of an affected individual coming into contact with a susceptible individual." This definition can be used for car traffic with the idea of crash risk being used instead of disease. Crash risk refers to the probability of a crash occurring in a traffic system. The core concept behind this is that herd immunity has both primary and secondary effects. The primary affects concern the direct protection that CAVs provide, and the secondary effects are the protection of the entire group due to a certain percentage of CAVs being part of that group. The group becomes more resistant to crash risk due to the CAVs being able to absorb the mistakes made by human drivers. This is the case if CAVs are proved to reduce the crash risk of everyone on the road. Considering that the concept of herd immunity can be applied to car traffic, additional research was done to determine the effects that CAVs can have on different safety metrics. A distinguishing factor between safety metrics was what type of information was considered when calculating their separate values. Most safety metrics are temporal or spatial by nature, which looks at the absolute value of speeds, times, or distances between vehicles. There was one safety metric that made use of a behavioural factor. CAVs affect this behavioural factor because they are assumed to have perfect driving, which is also why this safety metric was used for the simulation model so that there was another way to distinguish between human drivers and CAVs. From the literature review itself, it indicates that CAVs are theorised to always have a positive effect on the safety of car traffic. Most papers claim that the crashes occur due to human influence.

The literature was primarily responsible for determining the differences between driving behaviour of a CAV and an HDV. For simulation purposes these differences are straightforward. Bian *et al.* [22] (2019) mentions that the reaction time of a CAV is the time needed for the CAV to respond to the actions of the vehicle it is following. Practically this time can be considered zero because it is assumed to be near instantaneous. At the rate at which information travels, even at longer distances, the total time taken should remain very low.

Moving on, more decisions had to be made regarding the simulation model, and how CAVs can impact the decisions made for that. Starting off with driving behaviour, this is the largest differentiating factor between humans and CAVs. Humans have a reaction time and CAVs do not. More than that, CAVs prefer different following distances when following separate vehicles. CAVs exhibit cautious driving when following a human and can follow more closely when following another CAV. This impacted the choice on which car-following model to use because it needed to be able to include reaction times as well as headways. This was found in the Intelligent Driver Model+. Lane-change models were also researched to find out the effects that CAVs can have on the safety of those manoeuvres. Many crashes occur during lane changes and CAVs would reduce this by communicating the extra turbulence to upstream vehicles, which could influence their own driving to solve the disturbance quickly. What each of these studies agrees is on is that there are benefits for traffic safety to be gained by introducing CAVs into road traffic.

Simulation Model

The results found from the simulation model agree with the potential safety improvements. On the higher penetrations of CAVs not only do the number of conflicts reduce, but also the severity of these conflicts. A lot of the most severe conflicts occurring for HDVs was made more mild at the higher penetrations, but it does mean that the overall crash risk is reduced drastically. While these main results do indicate benefits, it only shows these benefits in a limited scenario with variables that remain static throughout. These benefits are in line with what was hypothesized. The literature agrees that CAVs would only have positive effects on the number of conflicts. For the core concepts of herd immunity, CAVs do reduce the crash risk of everyone on the road, which means that the secondary effects that are necessary for herd immunity for CAVs are proved. As the penetration rate of CAVs increases, the number of conflicts and their severity decreases. These benefits originate from the different driving behaviours assigned to the vehicle types. Both reaction time and headways have a huge impact on the differences in the number of conflicts that occur. During calibration in Chapter 3 these inputs were tested to determine what would be the optimal values for the simulation model. During calibration it seemed that optimal human reaction time would be appropriate for this simulation model because increasing that time ensured that conflicts would occur without a disturbance present. Therefore, the inherent crash risk would be too high if the reaction time was too high. Stability in the simulation model would not be reached quickly and would increase the simulation time substantially. The calibration for the headways follows a similar story, increasing the headways ensured a significant increase in the simulation time due to the stability taking longer. Ultimately an optimal headway of 1 second was used to optimise simulation time as well as portray the best human behaviour. Using optimal reaction times and headways for humans makes the decrease in conflicts at higher penetrations more significant.

The different conflict thresholds did play a role in counting the total number of conflicts. It is entirely possible to change these thresholds to focus on a different relative safety field strength. Focusing on different thresholds could shed light on where each conflict takes place. For example, reducing the relative safety field strength ranges to 0.1 can better show at what value each conflict occurs, but it runs the risk of providing too much information which would confuse rather than explain or detect trends. At the moment, the higher threshold is set at a relative safety field strength of 2.1, if this value would be higher, then there would be even fewer conflicts at 100%. The highest conflict value found was between an HDV following another HDV at 2.53. If a higher threshold value is taken then only conflicts between HDVs would be left which shows even more that the conflicts and their severity are decreased with the introduction of CAVs.

To test the effects of simulation inputs, a sensitivity analysis was done. The sensitivity analysis showed that the inputs can be changed to have a large effect on the immediate results. Changing the driving risk variable heavily impacted the number of conflicts, especially for the human drivers. The disturbance velocity also heavily impacted the number of conflicts, but this was for all types of following situations. Contrary to expectations, decreasing the maximum deceleration to the comfortable deceleration actually resulted in a decrease in the number of conflicts. Without the possibility of braking at 5 m/s^2 it was expected that the total number of conflicts would increase because the following vehicles might not be able to react quickly. This could be due to the homogeneous vehicle types and desired vehicle parameters (speed, disturbance velocity speed, maximum acceleration/deceleration, etc.). The only difference between vehicles at the moment is whether they are CAVs or HDVs. Exploring additional vehicle types with different settings would better reflect the realistic situation as driving behaviour should be heterogeneous rather than homogeneous. The same thing goes for the disturbance that is used. Although a certain desired velocity is provided for most vehicles, following that exactly is not how human drivers would function. Assigning a varying desired speed to the vehicles is a method in which the behaviour can become more realistic, even for CAVs.

For both the sensitivity analysis and the initial simulations, the penetration rate had a direct effect on the number of conflicts. The total conflicts decreased and their severity was lessened at every step that the penetration increased. The most notable penetration was at 65%. Here there were the fewest conflicts. This was dependent on the conflict thresholds used. For the total number of conflicts the conflicts started at a relative safety field strength of 1, when this could have been an entirely different value as well. Interestingly even, at 65% the conflict severity of 1-1.5 had one of the higher number of conflicts. By increasing the lowest threshold for the conflicts, 65% would show even fewer conflicts. This goes against expectations as it would be expected that the higher penetrations would provide the fewest conflicts. This can be explained by that at the penetrations of 80 and 90% each HDV has a significant impact on the number of conflicts. At a relative safety field strength of more than 1.8 and penetration rate of 90%, around 20% of the conflicts occur with an HDV involved. At 80% penetration, around 30% of the total conflicts contain an HDV. This could be an explanation as to why the higher penetrations have more conflicts than 65%. For 100% penetration, the fewest high severity conflicts take place, which goes in line with expectations, but it has more milder conflicts in comparison. This results in it having more conflicts than at lower penetrations. This could be due to the lower desired headway that all CAVs exhibit when following other CAVs. The disturbance causes more mild conflicts which increases the total number of conflicts for a 100% penetration rate.

In summary, the results of the simulation model generally followed expectations. Most unexpected situations stemmed from the ranges of the conflict thresholds. When only looking at the most severe conflicts, expectations were followed as CAVs reduced the total conflicts that occurred. Only at the milder conflicts did this not necessarily prove to be true. Defining the conflict thresholds was therefore a large part of evaluating the results. Ignoring the lowest threshold range of 1-1.5 could provide different results for the total conflicts. The sensitivity analysis showed that the robustness of the simulation could be lacking due to the significant changes in the number of conflicts. Changing the input values has a sufficient impact to consider separate scenarios to discover what happens at all conflict thresholds when the inputs are changed.

5.3. Limitations of the research

The limitations of the research were caused in a large part by the exploratory nature of this thesis. Simulating CAVs has definitely been done before with other studies, but this is one of the first to look at the concept of herd immunity for car traffic. There was little to no previous research to compare this to. Especially the safety metric of safety fields has seen such limited use that there was limited information about what the safety field strength actually means. The relative safety field strength and the conflict thresholds were concocted for this research specifically to be able to compare CAVs to HDVs. This is a limitation in the sense that it will not work for all future studies. It was dependent on the specifics of this research. Another limitation apparent in this research is the lack of additional scenarios. Although the sensitivity analysis did provide some insight into what would happen when the input variables are changed, it was not explored as thoroughly as another scenario would have been. This lack of extra scenarios makes the study quite limited, but it does achieve the goal of proving the concept of herd immunity for car traffic in this specific scenario.

Another limitation that the research contains is a more global limitation for testing safety with vehicle simulation. A simple car-following simulation model which uses IDM+ lacks the ability of simulating crashes. It is only possible to collect a value dependent on the safety metric being used. While it was checked whether any of the headways were lower than 5 meters (to denote a critically dangerous situation), IDM+ ensures that the simulated vehicles perform well and do not get into critically dangerous situations even with a reaction time being added. This connects to the limitation of the homogeneous nature of the vehicle types. Including more vehicle types will better reflect realistic scenarios. Car traffic is by nature heterogeneous, but due to just having two vehicle types (CAV and HDV), all the vehicles behave similarly. This starts the discussion on the limitations of the car-following model. IDM+ provides some benefits compared to the normal IDM by introducing two separate states (free acceleration and deceleration strategy), it still limits exactly what is used to determine speed. The model makes use of headway and vehicle speeds to determine the new acceleration when this is not something a human driver knows with 100% certainty. When driving, humans are affected by more than just the vehicle they are following, but also by the direct surroundings, which is not something that is used in this simulation model. For the purpose of this research, it is not necessary that this is done, but it does take away from the supposed realistic nature of the simulation model.

Driving behaviour is another way in which the simulation model is limited. Driving behaviour of an HDV is difficult to define because every person's driving behaviour is different. On top of that, driving behaviour for a CAV can only be presumed and not completely certain. Determining the driving behaviour for humans as well as CAVs is a limiting factor in this research. For the simulation model the two behaviours were distinguished by their headways, 'driving risk' values, and reaction time. It is unknown how exactly CAVs of levels 4 and 5 will act because it has not been fully developed yet. As it stands, using IDM+, changing these factors is the most effective way of distinguishing between the two types of driving behaviour and is also more than sufficient for the purpose of this research. So although this is a limiting factor for the research, it is a limiting factor for all research regarding the driving behaviour of CAVs and humans. This leads to the next limitation which is the number of assumptions made during the research. The driving risk variable for safety fields is one where an assumption is made that directly impacts the number of conflicts as shown by the sensitivity analysis. This and the other assumptions made during this research are unavoidable for a couple of reasons. One of these reasons is that human driving behaviour is difficult to quantify. Each driver has a unique driving style that is not possible to effectively incorporate into IDM+. Therefore, it was assumed that all human drivers had a homogeneous driving behaviour as well as all CAVs having a homogeneous driving behaviour. Another reason why the assumptions are unavoidable is that not enough is known about the true driving behaviour of CAVs. There are only indications to what their driving behaviour should be, but due to the lack of CAVs on the road currently, there is little information on their true driving behaviour.

The results themselves have some limits. The simulation model makes use of 28 different seeds in order to vary the vehicle orders to obtain different types of vehicle following situations. It is not easily possible to discover outliers when using this many different seeds. Nonetheless, these seeds were necessary to obtain statistically significant results but it could make it possible to miss blatant outliers or other anomalies. Other than that the results are quite direct in reporting the number of conflicts that occur. This is a strength as it shows exactly how the varying penetrations have an effect on the safety of the simulation model.

5.4. Recommendations

Further research is necessary especially to determine whether the concept of herd immunity still holds true for other situations with different vehicle inputs and traffic volumes. This was a small scale simulation where the conflicts were over a short distance with a small traffic volume. More information can be gained when the scale of the simulations increases, perhaps the second order effects of herd immunity have an even larger impact when more vehicles are involved. The same holds true for a scenario with lane changes. Lane changes can be detrimental to road safety. They increase the overall turbulence existent on the road. Providing a scenario with an incentive for lane changes could offer a better view whether herd immunity would continue to function in such a scenario.

Another aspect to research further is the number of vehicle types that are simulated. The simulations could benefit from introducing more driving behaviours for humans and for CAVs to see how this would affect the conflicts. This would be done in order to better reflect reality as there is no one manner in which humans drive. These could be split simply into cautious, normal, and risky driving styles. Something that was definitely out of the scope of this project is to use an artificial intelligence car-following model. What this would provide is heterogeneous behaviour among both the CAVs and the human drivers. In turn, it also provides the most realistic simulation possibilities. The different vehicles types can also incorporate different vehicle inputs. That some vehicles use comfortable acceleration/deceleration whereas others would use the possible maximum values.

Further studies should focus on extending the research on safety fields. This paper provides a method in which the safety fields of different types of vehicles can be compared. It could be valuable for future research regarding CAVs to be able to judge the severity of certain conflicts. This paper provides a possible baseline to be used in future research. Other papers can make use of the idea of a relative safety field strength rather than the absolute values. Further simulation work with safety fields would benefit both simulation work and safety work as more reference work is created. Safety fields has a lot of potential for future work because the safety metric has a lot of potential. Being able to map the behavioural field and static field on top of the dynamic field offers so much more than a standard safety metric for vehicle simulation. The driving process has so many aspects that can affect the safety of the road, that safety fields is one of the metrics that incorporates the most of these aspects and future research into safety fields would be incredibly beneficial.

6

Conclusions and Recommendations

This chapter concludes the research on simulating CAVs (Connected Automated Vehicles) with the concept of herd immunity in mind. The purpose of this chapter is to answer the research questions discussed in Chapter 1 as well as summarise and reflect on the research.

6.1. Conclusions

This research was aimed at answering the following research question, **How is traffic safety influenced by connected (automated) vehicles considering the concept of herd immunity?**. This concept has never before been considered for car traffic and the innovation of CAVs could make it a reality. The principle of herd immunity required an impact assessment to determine how much the safety of the road could be affected.

Through an extensive literature review and simulation model this thesis has shown how traffic can be influenced by CAVs as well as how the concept of herd immunity can be translated to road traffic. To do that, the driving behaviour differences between CAVs and human drivers had to be defined for there to be any difference between the two. According to the literature, the main difference between a human driver and a CAV is that CAVs do not make human errors. This difference translates to the model by them having a reaction time of 0 seconds as well as a driving risk variable value of 0, denoting perfect driving. Next, the concept of herd immunity had to be defined. For a virus this is based on viral risk, whereas for car traffic it is defined by crash risk. For herd immunity to function for car traffic, a clear secondary effect needed to be defined. The inclusion of CAVs should ensure that the entire group of vehicles is made safer. The CAVs need to absorb the mistakes made by humans to reduce the total crash risk in their direct environment as well as upstream. Not only do the CAVs improve the safety of themselves, but also those around them. For this concept to be proved, it was necessary to show second order effects in the simulation model. The literature review backed the idea that CAVs could have huge safety impacts, but without evidence, it only theorises the benefits.

Additionally, in the literature review, focus was put on the type of car-following and lane-changing model that should be used when modelling CAVs. For the purpose of this research, only the car-following model was used in the simulations. The lane-change models were researched in part to determine how lane-changes affect the level of safety of a road and how CAVs could alleviate any dangers. After reviewing many possibilities, IDM+ was considered the most effective for the purpose of the research. It provides clarity on the decisions made by each vehicle and was straightforward to implement. To use this in conjunction with CAVs, a reaction time was introduced into IDM+ as well as different headways being used depending on the following situations. To measure the level of safety of the road, safety metrics are often used. Many of these are straightforward and calculate values like a time-to-collision. Many of these safety metrics are suitable for this project, but there was one safety metric that implemented driving behaviour differences which made it stand out in comparison to the rest. This safety metric is called safety fields. Safety fields make use of three different fields in order to measure the level of safety of a road. The higher the safety field strength gets, the more likely a crash is going to occur. This was considered most suitable for the simulation model because it makes use of the behaviour differences between CAVs and human drivers.

The simulation model showed that there were benefits to be gained from CAVs in car traffic. Using the differences in driving behaviour, the CAVs not only reduced the total number of conflicts when compared to other penetrations, but also reduced the severity of those conflicts. Reducing the severity of the conflicts is what helps prove the concept of herd immunity for car traffic. The most critical conflicts occurred far less frequently at 100% penetration when compared to any other penetration. When considering all defined conflicts, a penetration rate of 65% showed the fewest conflicts, but still far more critical conflicts than at 100%. The combination of reducing the total number of conflicts along with their severity is what shows that the concept has merit. There is no clear tipping point at which the level of safety improves drastically, but this is due to the number of conflicts decreasing at an almost linear rate. The main evidence that points to herd immunity having merit for this scenario is that the number of severe conflicts decreases heavily as the penetration rate increases. If a tipping point would have to be defined, it would be at the 65% penetration as it has the fewest total conflicts. After this the number of conflicts might increase, but their severity decreases.

To return to the main research question, traffic safety is positively influenced by the introduction of CAVs. As demonstrated by the results from the literature review and the simulation model, the number of conflicts decreases as well as the severity of those conflicts. Herd immunity applies to this specific scenario of the simulation model due to both the primary and the secondary effects of herd immunity being satisfied. There are almost 8000 fewer critical conflicts (conflicts above a 2.1 severity level) at 100% penetration compared to there being 0 CAVs. This evidence shows that for this scenario, herd immunity would apply and have great safety benefits. Furthermore, the reviewed literature supports this assessment as many papers claim that all human error can be eliminated through the introduction of CAVs.

6.2. Recommendations

Although recommendations were made in Chapter 5, this section looks at the implications of the research as well as reflects on the research done.

Safety fields were used to judge the change in safety over all the penetration rates, and it has shown that it is a valid safety metric. By using the relative safety field strength it was possible to compare the conflict values. It was a valid method of testing the safety for this specific situation. Safety fields is an area in which much more research can be done to make it a more commonly known safety metric. It shows such promise for future research because it looks at more than just the cars on the road. It makes it possible to include a static field as well, for simulation research into urban areas with different types of driving behaviour. The car-following model IDM+ was effective in that it did exactly what it was required to. It made it possible to differentiate between driving behaviours through the headways and the reaction times. On top of that, it was quite straightforward in its use and transparent, so that it was possible to determine the process at every step. It was the most appropriate car-following model to use in the situation.

The methodology for the simulation model was targeted specifically for creating a proof on concept. With that in mind, it successfully achieved what it set out to do. It should be mentioned though that there are a lot of possibilities regarding this topic. For further testing, additional scenarios should be created with additional tactical manoeuvres and making use of safety fields. From the conclusion it is clear that there are benefits to be gained from introducing CAVs onto this type of road, but there are more potential benefits to be gained when lane changes are present. This increase in the turbulence of the road is where CAVs could show even more how they could reduce the total number of conflicts as well as their severities. Next steps could include traffic control on top of the other tactical manoeuvres to introduce additional disturbances affecting the turbulence of the road. Each of these different test scenarios could finally lead to the concept being tested on real-life road traffic, but this could only be done when there are a sufficient number of CAVs on the road.

Another recommendation is targeted towards the driving behaviour that has to be defined for both humans and CAVs. The results showed that CAVs following HDVs resulted in zero conflicts above the threshold level of 1.5. CAVs used a more cautious following distance when following HDVs, but that cautious nature served the purpose of this research. Varying these headway values could be part of future research to determine the effects of this cautious behaviour. For improving traffic flow, lower headways could be considered for CAVs because they have a quicker reaction time than that of humans. In general, more research should be done on the driving behaviour of CAVs. Due to it being such an innovative technology, their true driving behaviour is still being developed and the literature on it is inconsistent.

Finally, returning to the problem statement, the principle of herd immunity is theorised to function for car traffic as it does for the spread of a virus. The research performed in this thesis was meant to provide a proof of concept for the principle of herd immunity for car traffic. The simulation model was supposed to provide an impact assessment to determine to what extent herd immunity could be applied to vehicle traffic. The literature study established that there was no previous knowledge on using this principle for car traffic and the results of the simulation model confirmed that herd immunity can be applied to car traffic. This proves that more research should be done to expand the knowledge on this topic. Crash risk was used as the "virus" during this research, but this can be explored further by defining different means by which the "virus" transfers. There are more options regarding this that do not just focus on the degree of turbulence, but rather specific mathematical models that could denote the spread of crash risk.

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A

APPENDIX

A.1. CAR-FOLLOWING MODELS

This section is used to describe a number of car-following models in further detail including their acceleration equations as well as some calibration methods per car-following model.

A.1.1. STIMULUS-RESPONSE MODELS

GHR model

The GHR model was created at the General Motors research laboratories simultaneously with Kometani and Sasaki in Japan. The model is shown by Equation A.1.

$$a_n = c v_n^m(t) \frac{\Delta v(t-T)}{\Delta x^l(t-T)} \tag{A.1}$$

Where:

- a_n: Acceleration of the (n)th vehicle at time t.
- c, m, l: Calibration parameters.
- v_n: Velocity of the (n)th vehicle.
- Δv: Relative speeds between the (n)th and the (n-1)th vehicles.
- Δx: Relative spacing between the (n)th and (n-1)th vehicle.
- T: Reaction time.

Much research has been performed to calibrate the model. Chandler *et al.* [25] (1958, as cited in Aghabayk *et al.* [24], 2015) proposed that m and l should be equal to zero, but later studies (Edie [46], 1961, as cited in Aghabayk *et al.* [24], 2015) found that the calibration would improve if the parameters were set to 1. This model did not take braking into consideration and that was put into the linear model, otherwise known as the "Helly" model. The GHR model also does not limit the acceleration and the deceleration, when in reality, these are limited by the vehicle.

Linear model

The linear model added some terms into the first GHR model to deal with the braking of a leading vehicle. The model simplifies to Equation A.2.

$$a_n(t) = c_1 \Delta v(t-T) + c_2 [\Delta x(t-T) - D_n(t)] \tag{A.2}$$

Where:

- a_n: Acceleration of the (n)th vehicle at time t.
- Δv: Relative speeds between the (n)th and (n-1)th vehicles.
- Δx: Relative spacing between (n)th and (n-1)th vehicles.
- T: Driver's reaction time.
- c_1, c_2: Model calibration parameters.
- $D_n(t)$: Desired following distance formulated by Equation A.3.

$$D_n(t) = \alpha + \beta v_n(t-T) + \gamma a_n(t-T) \tag{A.3}$$

Where:

- v_n: Velocity of the (n)th vehicle.
- α, β, γ: Calibration parameters

This model was calibrated by using a wire linked vehicle for both congested and uncongested traffic conditions (Hanken and Rockwell [47], 1976, as cited in Aghabayk *et al.* [24], 2015). This model and the GHR model were both calibrated many times to obtain the ideal calibration parameters, but a number of issues get raised with both of these models. Brackstone and McDonald [48] (1999) mentions that one main difference between the GHR model and the Linear model is that the Linear model is able to derive a desired distance relationship which is consistent through previous calibration attempts. A major strength of the Linear model is the inclusion of a possible 'error'. The model may be implemented so that when a certain acceleration has been calculated, that it does not change until there is a sufficiently large change in Δx or Δv. This better represents human driving behaviour and is an advantage over the GHR model.

Optimal Velocity model

The Optimal Velocity model takes the difference between the desired velocity and current velocity as the stimulus for the driver's actions (Aghabayk *et al.* [24], 2015). This model is represented by Equation A.4. Equation A.4 represents the driver's response.

$$a_n = c\left[V_n^{\text{desired}}(t) - v_n(t)\right] \tag{A.4}$$

Where:

- a_n: Acceleration of the (n)th vehicle at time t.
- V_n^{desired}: Desired speed of the (n)th vehicle.
- v_n: Velocity of the (n)th vehicle.
- c: Model calibration parameter.

The acceleration of the following vehicle is different. This is shown by Equation A.5. This model takes more into account than just the leading vehicle. It takes the relative spacing of the two successive vehicles into account.

$$a_n(t) = c\left[V^{\circ\text{opt}}(\Delta x(t)) - v_n(t)\right] \tag{A.5}$$

Where:

- Δx: Relative spacing between the (n)th and (n-1)th vehicles.
- $V^{\text{opt}}(\Delta x)$: A sigmoid function of Δx represented by Equation A.6.

$$V^{\text{opt}}(\Delta x) = \begin{cases} 0 & \Delta x < \Delta x_A, \\ f(\Delta x) & \Delta x_A < \Delta x < \Delta x_B, \\ v_{\max} & \Delta x_B < \Delta x. \end{cases} \tag{A.6}$$

In order to use the Optimal Velocity model it is necessary to calibrate the model using Equation A.6. The Optimal Velocity model suffers from the same problems as all the other stimulus-response models and could also introduce very large acceleration rates (Nagel *et al.* [49], 2003, as cited in Aghabayk *et al.* [24], 2015). Due to those flaws, the model has not been used extensively.

A.1.2. Collision Avoidance Models

Kometani & Sasaki

Kometani and Sasaki created a model based on a safe following distance using physical motion equations (Kometani and Sasaki [32], 1958, as cited in Aghabayk *et al.* [24], 2015). This model claims that a collision becomes unavoidable when a leading vehicle moves unpredictably and the following vehicle is within the safe following distance described by Equation A.7.

$$\Delta x(t-T) = \alpha v_{n-1}^2(t-T) + \beta_1 v_n^2(t) + \beta v_n(t) + b_0 \tag{A.7}$$

Where:

- $\Delta x = x_{n-1} - x_n$: Relative spacing between the (n)th and (n-1)th vehicles.
- v_{n-1}: Velocity of the (n-1)th vehicle.
- v_n: Velocity of the (n)th vehicle.
- T: Driver reaction time.
- $\alpha, \beta_1, \beta, b_0$: Model calibration parameters.

Gipps

As described in Gipps [33] (1981), Gipps created a model that is based on collision avoidance depending on two constraints for the follower's velocity.

- The speed of the following vehicle should not exceed its desired speed and its free acceleration should first increase with speed as engine torque increases and then decreases to zero as the follower approaches the leader.
- The follower must be certain that an emergency brake is possible if the leader were to make a sudden braking manoeuvre. In previous models of this type there was no margin for error and therefore a reaction time was included equal to T/2, where T is the reaction time.

This resulted in the following formulation of the equations (Equation A.8). (Gipps [33], 1981)

$$v_n(t+T) = \min \begin{cases} v_n(t) + 2.5 a_n T\,(1 - v_n(t)/V_n)\,(0.025 + v_n(t)/V_n)^{1/2} \\ b_n T + \left\{ b_n^2 T^2 - b_n \left[2\,(x_{n-1}(t) - s_{n-1} - x_n(t)) - v_n(t) T - v_{n-1}^2(t)/\hat{b} \right] \right\}^{1/2}, \end{cases} \tag{A.8}$$

Where:

- a_n: Maximum acceleration that the driver of vehicle n would want to use.
- b_n: Maximum braking that the driver of vehicle n is willing to undertake.
- s_{n-1}: Effective size of the leading vehicle.
- V_n: Desired speed of vehicle n.
- $x_n(t)$: Location of vehicle n at time t.
- $v_n(t)$: Speed of vehicle n at time t.
- $\hat{b}$: Estimation of b_{n-1} employed by the driver of vehicle n.

A.2. ADDITIONAL RESULTS

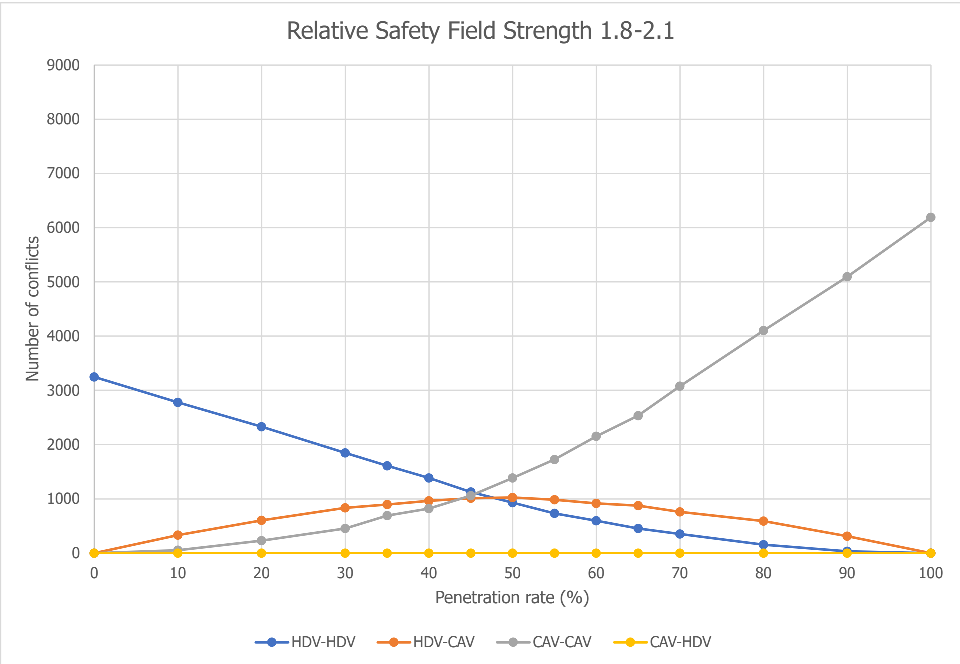

Figure A.1: Relative safety field strength threshold between 1.8 and 2.1

Figure A.1 is put into the appendix because it could give the wrong idea about the number of conflicts that occur. Due to it not being a complete picture, it does not illustrate that most critical conflicts are reduced to this conflict range.